

YIXIN LU

Data-Driven Decision Making in Auction Markets



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Data gedreven besluitvorming in veiling markten

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To my beloved parents, Wei and Julian

Acknowledgement

Back in Spring, 2009, I was struggling with the decision of whether to do a PhD in statistics or computer science, because they seem to be the most “reasonable” choices given my background. Then, I met an old friend who introduced me to the fascinating book by Dan Ariely, “*Predictably Irrational: The Hidden Forces That Shape Our Decisions*”. It was this book that refreshed my mind completely and led to my final decision to pursue a PhD on human decision-making rather than dancing with the numbers and symbols all day in the next years¹.

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¹“Ironically”, a large part of this dissertation is still about numbers and equations, :)

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Den Haag, May 2014

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Chapter 1

Introduction

The past two decades have seen an explosion of digital data in every sector of the global economy¹. According to the research firm IDC, from 2005 to 2020, the global volume of data will grow by a factor of 300, from 130 exabytes to 40,000 exabytes, or 40 trillion gigabytes. Such a revolution from data scarcity to data abundance brings great opportunities to businesses across the world.

In particular, the increased accessibility of data has enabled a different way of making decisions that involves more empirical evidence rather than personal experience, intuition, or belief. Such a new practice of “basing decisions on the analysis of data rather than purely on intuition” has been coined as *data-driven decision making* (Provost and Fawcett, 2013), and there has been a growing interest in its promises across different domains. For example, as a leading player in the retail industry, Walmart has pioneered the data-driven practices in analyzing data from multiple sales channels, catalogs, stores, demographic and online interactions to tailor product selections and determine the timing of price markdowns. The Internet giants such as Google and Facebook are customizing their services by mining users’ internet browsing activity. The more traditional sectors such as manufacturing are also leveraging the power of data to improve efficiency and sustain the growth.

Previous studies have shown that companies that adopted a data-driven approach are more productive and profitable than their competitors (Brynjolfsson et al., 2011). In this research, we focus on the value of data-driven decision making at market level and seek to illustrate and quantify its benefits in the design and operationalization of auction markets.

¹For more details, see “A special report on managing information: Data, data everywhere,” *The Economist*, February 25, 2010.

1.1 Motivation

Auctions play a critical role in the modern society: governments use auctions to sell treasury bills, mineral rights and many other assets; firms use auctions to subcontract work, buy services and raw materials; individuals also participate in auctions of various consumer products such as art, antiques, cars, or even houses (Klemperer, 1999). The Internet has expanded the scope and reach of auctions tremendously: by breaking the physical limitations such as geography, time, and space, online auctions open up vast new opportunities for businesses of all sizes and become an indispensable part of the new economy (Bajari and Hortaçsu, 2004).

Despite the great promise they hold, online auctions also pose many new challenges for practitioners and academics. For example, Bapna et al. (2001) point out that the behavior of the different economic agents in auctions is heavily influenced by the online context in which they take place. As the result, many of the elegant and powerful results from the classical game-theoretic analysis of auctions do not apply any more. Dealing with these complications requires not only careful attention to the institutional details of these emerging markets, but also new analytical and computational tools to supplement the traditional game-theoretic or decision-theoretic models (Rothkopf and Harstad, 1994).

Over the past decades, Information Systems (IS) researchers have made significant contributions to practical auction design by investigating different bidding strategies and price dynamics in real-world auctions. For example, Kauffman and Wood (2006) studied the auctions of rare US coins on eBay and found that bidders tend to increase their bids for the same item if others also express interests in the item. More recently, Goes et al. (2010) examined the evolution of bidders' willingness-to-pay using a large dataset from Sam's club auctions. They demonstrated that bidders update their willingness-to-pay in sequential auctions based on their demand, participation experience, the outcomes in previous auctions and auction design parameters.

Further, researchers have made considerable progress in the development of computational tools to facilitate decision making in complex auction markets (Adomavicius and Gupta, 2005; Adomavicius et al., 2009; Ketter et al., 2012; Mehta and Bhattacharya, 2006). This has given rise to the novel, interdisciplinary research area, namely, *smart markets* (Bichler et al., 2010; McCabe et al., 1991). The primary goal of smart market research is to develop theoretically guided computational tools to understand the characteristics of a complex trading environment and facilitate real-time decision making in these complex environments (Bichler et al., 2010). Our current research shares a similar initiative by systematically examining real-time decision making in complex auction markets.

1.2 Research Question

In light of the pervasive adoption of data-driven approaches in auction research, we raise the following research question: *how to leverage the power of data to improve the performance of complex auction markets?*

Prior research has proposed different performance criteria such as allocative efficiency and revenue maximization (Krishna, 2002). However, since in most real-world auctions bidders never reveal their private values, it is impossible to compute the allocative efficiency of given auctions. In this research, we use revenue maximization as the key performance measure.

Given the complex interplay of different informational and strategic factors in these markets, we conduct three specific studies to address this research question. The common thread linking these studies is the focus on the real-time interaction between auctioneers and bidders.

Our first study examines how auction design parameters affect bidders' real-time decisions and market processes. We derive a structural econometric model (Paarsch et al., 2006) which allows us to conduct policy counterfactuals to assess the effectiveness of alternative auction designs. Based on the estimation of the structural properties, we also develop a dynamic optimization approach to guide the setting of the auction design parameters.

The second study explores bidding strategies across different market channels using a unique and extensive data set from a complex B2B market. In addition to identifying and characterizing the bidding strategies, we also examine the antecedents and consequences of these strategies, as well as their interactions with auction design parameters. This study complements the existing literature on bidder heterogeneity in business-to-consumer (B2C) markets (Bapna et al., 2004; Goes et al., 2012).

In the third study, we focus on the information transparency issues in sequential auctions. Different from most of the previous studies on information revelation policies in auctions which are purely analytical, we conduct a field experiment to examine the effects of different information revelation policies on price dynamics and market performance. Specifically, we compare the bidding dynamics under two settings: the high-transparency setting where winners' identities are revealed publicly and the low-transparency setting where winners' identities are kept hidden from public view. The findings from this study provide useful implications for the design of information policies in multi-channel markets.

1.3 Methodology

We adopt a multi-method approach to address the main research question. The rationale for choosing such multi-method approach is that each research method has its strengths and weak-

nesses and the combination of multiple methods can provide richer and more reliable results (Mingers, 2001). In the following we briefly describe each of the methods used in this research. The methodological details of the individual studies will be discussed in the respective chapters.

Structural Modeling. Structural modeling has become increasingly popular in auction research over the past decades. By assuming that all the observed bids are the equilibrium bids of the auction model under consideration, the goal of structural modeling is to identify the structural properties of the auction model, particularly the underlying distribution of bidders' values. The identification of these structural properties can be used to evaluate a given auction format and study the policy counterfactuals, i.e., how changes in auction rules would affect sellers' revenue and market clearing speed.

Simulation. With the advance of computational power, simulation has been used in a wide spectrum of research. Different from conventional research methods which focuses on answering "What, how and why" questions, simulation allows us to assume the inherent complexity of organizational systems as given and helps answer the "What if" questions. In particular, market phenomena that are too complex for conventional analytical or empirical approaches can be addressed by simulation methods. For example, McMillan (2003) conducts various simulations to understand the performance of different market designs. In our case, we use simulation together with structural modeling to provide normative insights for the design and operationalization of sequential B2B auctions.

Statistical Machine Learning. As the natural outgrowth of the intersection of Computer Science and Statistics, statistical machine learning techniques allow us to identify patterns of large-scale, dynamical data streams arising from various application domains (Hastie et al., 2009). In this research, we use both parametric and non-parametric methods to understand bidders' decisions in a complex auction market. Compared to the structural modeling, statistical machine learning prioritizes the goodness-of-fit to the empirical data.

Field Experiment. Experiments are useful to make causal inference about certain effect. Despite its increased external validity, field experiments are much less used than lab experiments when studying market design. This is mainly due to the extremely high cost and difficulties in conducting controlled, randomized trials in the field of interest. We are fortunate to team up with the policy makers of a large Business-to-Business (B2B) market and had the opportunity to conduct a large-scale field experiment on information revelation policy.

1.4 Structure

The rest of this dissertation is organized as follows. Chapter 2 provides a detailed introduction to the research context, namely, the Dutch Flower Auctions. Chapter 3, 4 and 5 are three specific studies that address the central research question from different angles. Finally, Chapter 6 summarizes the contribution of this research and discusses the limitation and future work. Figure 1.1 provides an overview of the structure of this dissertation.

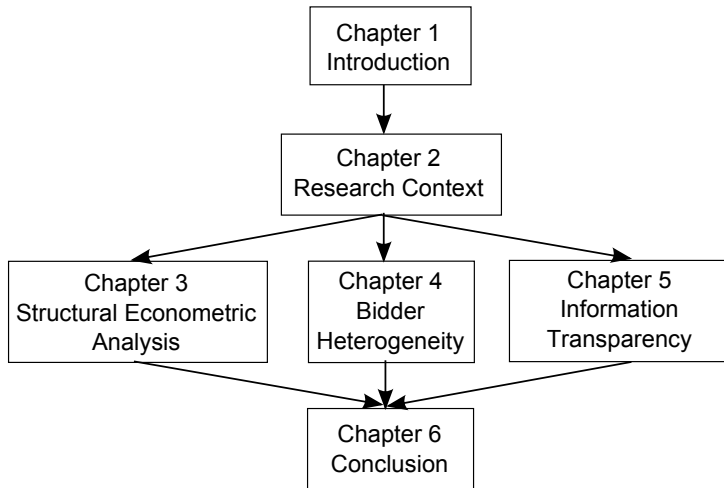


Figure 1.1: Structure of the Dissertation.

Chapter 2

Research Context

The empirical data used in this research are obtained from the largest wholesale market of cut flowers and ornamental plants in the world, namely, the Dutch Flower Auctions. In this chapter, we will first justify the choice of this empirical setting and then introduce this specific auction market in detail.

The primary reason for choosing the Dutch Flower Auctions as the research context is that they add real-world complications to the decision-making process in classical auction models. For example, bidders can demand multiple units in each round of the sequential auctions (see Section) and both bidders and auctioneers have to make their decisions within a few seconds. They also highlight the important transformation of moving from place to space, which transcends the particular market practices. Finally, the Dutch Flower Auctions are worthy of attention in their own rights given their significant economic and social importance.

2.1 The Dutch Flower Auctions

The Dutch Flower Auctions play a critical role in maintaining the Netherlands' leadership in the floriculture industry (Kambil and van Heck, 2002). They account for more than 60% of the global flower trade. In 2012, the total turnover of the auctioned products (i.e., cut flowers, indoor and outdoor plants) is approximately €4.4 billion¹. Some of the flowers originate in the Netherlands, but many originate in countries like Columbia, Ethiopia, Kenya, and Zimbabwe. In the late afternoon, domestic growers send their flowers to the main auction sites². Meanwhile, planes loaded with imported flowers land at the Schiphol airport near Amsterdam. Later in the evening, the *fresh* products are transported to refrigerated rooms in the auction sites where the flowers are sorted and grouped in similar types. These include well-known products such as

¹The turnover of cut flowers is over €2.4 billion.

²Currently, there are 5 auction sites within the country: Aalsmeer, Naaldwijk, Rijnsburg, Bleiswijk and Eelde. There is also one auction site located at the Dutch-German border. However, the turnover from this auction site is not consolidated with the DFA totals.

roses, chrysanthemums, lilies and tulips in various categories as well as niche products such as matricaria. The quality of the flowers is inspected by professional appraisers. Many buyers also frequently visit the storage rooms to check the products in early morning before auctions start.

On weekdays, up to 40 auctions occur simultaneously from 6:00 a.m. to 10:00 a.m. Flowers are auctioned as separate lots, which are defined as the total supply of a given homogeneous product from a given supplier on a given day. The size of a lot can vary from a few units to more than a hundred units, and each unit consists of 20 to 80 stems, depending on the type and quality of flower. Buyers³ can either bid in the auction halls or via a remote bidding system which allows them to view, filter and even pre-mark the full range of flowers prior to bidding. At any time, an individual bidder, whatever bidding onsite or remotely, can only participate in one auction, however, an institutional buyer can delegate several bidders to the auctions running in parallel.

2.2 The Mechanism

The Dutch Flower Auctions use the Dutch auction mechanism. They are implemented using fast-paced auction clocks displayed on an electronic board. Aside from the current asking price, each clock also contains information about the setup of the current auction (for example, monetary unit, minimum purchase units as well as bundling properties). Further, bidders can also see the information of the product under auction (name of the product, identity of the grower, various quality indicators and a representative picture of the product) from the electronic board. Figure 2.1 provides an illustration of the clock interface.

At the beginning of an auction, the auctioneer decides the starting position of the clock which corresponds to a high price of the product, and sets the clock in motion. As the clock ticks down counterclockwise, each bidder can stop the clock by pressing a button indicating that she is willing to accept the price corresponding to the current clock position. The first bidder who makes a bid wins. The winning bidder, whose identity is shown on the clock screen, can select the portion of the lot being auctioned (which must exceed the minimum required amount). If the winning bidder does not select the entire available amount, the clock ticks backward and restarts at a high position, and the auction continues. This process repeats until the entire lot is sold, or the price falls below the seller's reserve price⁴, in which case any unsold goods in that lot are destroyed. Such multi-unit, sequential Dutch auctions operate in a time-efficient manner: on average, each transaction takes 3 to 5 seconds. Therefore, they are well suited to the wholesale market of flowers.

³Here buyers could be individuals or organizations.

⁴Currently, the reserve price is fixed for the entire year, regardless of auction site and flower types.

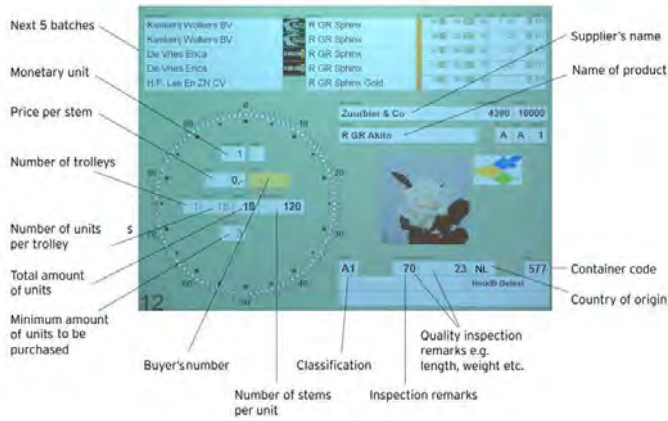


Figure 2.1: Illustration of the auction screen. The setup of the current auction is shown on the clock whereas the product information and the upcoming schedules are shown on the right and top-left of the screen, respectively.

Table 2.1 gives a stylized example of a sequence of transactions that can be found in our data set. In this example, a lot containing 18 units is sold. At the beginning of each round, the auctioneer sets the starting price and minimum purchase quantity (italicized in the table). The sales prices are not monotonically decreasing or increasing⁵. Also, unlike the existing studies which focus on the situation where only one unit is sold in each round, in our case, the purchase quantity in each round can vary a lot. Because bidders do not know *a priori* whether there will be units left after the current round of auction, they face much higher uncertainty in these auctions.

Table 2.1: A sample entry in a logbook. The auctioneer's decision variables are italicized.

Transaction Index	Transaction Time	Seller ID	Flower ID	Stem Length	Stems Per Unit	Available Units	<i>Minimum Purchase Units</i>	<i>Starting Price (cent)</i>	Buyer ID	Purchase Units	Price (cent)
171	08:10:54	5644	103668	70	50	18	1	100	439	2	22
172	08:10:56	5644	103668	70	50	16	3	41	395	5	20
173	08:10:57	5644	103668	70	50	11	4	39	439	7	21
174	08:10:59	5644	103668	70	50	4	4	40	563	4	20

⁵Van den Berg et al. (2001) show empirical evidence for declining price anomaly in the flower auctions; however, if we look at individual auctions, price trends are inconclusive in these multi-unit sequential auctions.

2.2.1 The Online Bidding Channel

In June 1996, the DFA introduced the remote buying application (KOA)⁶, an online bidding system that enables bidders to participate in auctions without being physically present in the auction hall. Initially, such online bidding channel only attracts a few large buyers for two reasons. First, KOA system requires a significant investment in hardware and software. This includes dedicated computers, communication system between the auction hall and the computers used for bidding as well as monthly subscription fee for approximately €220 in order to use the system. Second, large buyers have strong incentive to adopt such remote bidding system. Traditionally, large buyers need to have several bidders to follow auctions that run in parallel. Since KOA allows each bidder to effectively monitor several auction clocks at the same time, it can help the large buyers to save personnel costs.

Over the past few years, KOA has become a great success. Interviews⁷ with buyers revealed two major benefits brought by such online channel, the reduced travel costs and the enhanced monitoring capabilities. Some large buyers also point out that KOA allows them to better coordinate the purchases in the auctions and the sales to the end customers. Despite the enthusiasm of the buyers, results from previous studies are inconclusive with regard to the impact of KOA on winning prices.

2.3 The Auctioneers' Problem

The auctioneers in the Dutch Flower Auctions represent the growers. Therefore, an important goal of their work is to maximize the total revenue. Further, given the perishability of flowers, it is also critical to achieve a quick turnaround in these auctions. In fact, the total time for conducting the auctions has long been a hard constraint for the growth of the market. Auctioneers can influence the dynamics of the sequential multi-unit auctions by controlling the key auction parameters including clock speed, starting prices, minimum purchase quantities and reserve prices. The choices of these parameters often involve tradeoffs between revenue maximization and the total time need to finish the auctions. For example, by increasing the minimum purchase quantities, auctioneers can speed up the auctions quite substantially, yet such benefit often comes at a cost of revenue reduction (Lu et al., 2013).

Further, auctioneers can also influence the bidding competition by disclosing or withholding extra information about market states (for example, the number of bidders logged into the bidding system) during an auction. The (un)disclosure of certain information have both direct

⁶In Dutch, the Remote-Buying or Buying-At-A-Distance initiative is referred as KOA, the acronym of "Kopen op Afstand."

⁷We conducted several onsite interviews with buyers of different sizes during 2011 and 2012.

and indirect effects on bidding behavior in sequential rounds. First, bidders are able to use the extra information disclosed in the previous rounds to update their beliefs about their opponents and adjust their bidding strategies. Second, bidders might take into account such direct informational effect and strategically alter their behavior in the previous rounds⁸.

As more and more bidders adopt the remote bidding application and participate in the auctions via the online channel, the design and implementation of information policies, particularly the information revelation policies become increasingly critical to the revenue generation of these auctions. For one thing, the online channel allows more bidders to participate in the auctions and significantly increases the market-level uncertainty. For another, it also allows bidders especially the large buyers to better coordinate their bidding activities across different auction sites⁹. Unfortunately, however, due to the limited availability of proprietary data, there is a lack of normative insights that may inform or guide the design of these information policies.

⁸Such direct and indirect effects are related to bidders' learning in sequential auctions which has been studied in Jeitschko (1998). However, our main focus is the auctioneer's role in such learning process.

⁹The auction schedules at different sites are not synchronized and there is indeed potential for arbitrage.

Chapter 3

Structural Econometric Analysis of Sequential B2B Auctions¹

3.1 Introduction

Auctions have long been used as effective mechanisms for price discovery and resource allocation. Beginning with the work of Vickrey (1961), a large body of literature has investigated various informational and strategic factors in auction design using the game-theoretic framework². Despite its sharp predictions about the optimal way to design and conduct auctions, most of the theoretical work focuses on stylized settings and rarely considers the real-world operating environment (Rothkopf and Harstad, 1994). This highlights the necessity of studies addressing the gap between the predictions derived from classical auction theory and the practical auction design.

The proliferation of online auctions has spawned a wide stream of empirical research on real-life bidding behavior and practical auction design (Bajari and Hortagsu, 2004). However, most of the empirical work has exclusively focused on B2C or C2C auctions. Comparatively, little attention has been paid to B2B auctions which usually involve professional or expert bidders and carry much higher economic stakes³. Further, the existing studies often take the reduced-form approach which aim to characterize bidder behavior in auctions rather than to use the

¹This chapter is based on two conference papers “Designing Intelligent Software Agents for B2B Sequential Dutch Auctions: A Structural Econometric Approach” and “Applying Structural Econometric Analysis to B2B Sequential Dutch Auctions”, co-authored with Alok Gupta, Wolfgang Ketter and Eric van Heck, and is currently under review at a top-ranked journal in management. The author of this dissertation is the first author of these papers. We thank the seminar participants at Carlson School of Management and the Wharton School, at the Conference on Information Systems and Technology (CIST 2013), International Conference on Information Systems (ICIS 2013), and at the Statistical Challenges in eCommerce Research Symposium (SCECR 2013) for feedback and discussions. The authors acknowledge the comprehensive support from FloraHolland.

²For a survey of the literature, see Part A of Klemperer (1999)

³According to a recent report by Forrester, by the end of 2013, customer-facing front-end B2B eCommerce in the US will reach \$559 billion, while the B2C market will bring in less than half that at \$252 billion.

bidding function to map the observed bids to bidders' valuations. For example, using bidders' behavioral variables such as entering time and bidding frequency, Bapna et al. (2004) uncover the pattern of buyers' bidding strategies in an online B2C environment. Despite its popularity, such reduced-form approach, however, is not able to predict the effects of policy changes in bidding procedure. This is because such policy changes often constitute changes of individual bidder's strategic behavior as well as their interactions. For example, as Arora et al. (2007); Kannan (2012) have shown that changes on information revelation policies have strong impact on bidders' strategies in sequential auctions.

To address these research gaps, we adopt the so-called structural econometric approach (Paarsch et al., 2006) to study sequential auctions in a complex B2B market. Structural models, as opposed to reduced-form models, derive econometric specifications from economic theories where individuals or organizations are assumed to pursue profit-maximizing behavior. By explicitly recovering the key parameters of the derived models, for example, the parameters characterizing the distribution of bidders' valuations, the structural approach allows us to perform policy counterfactuals by simulating results under different auction designs, and thus be able to compare the expected performance of alternative designs.

Our paper makes three important contributions. First, we extend the existing structural models in empirical auction research (see Hickman et al. (2012) for a guide to the literature) to deal with sequential auctions where bidders can purchase multiple units of products in each round. Currently, most of the structural modeling work focuses on single-unit auctions, for example, Donald and Paarsch (1996); Guerre et al. (2000); Laffont and Vuong (1995); Paarsch (1997). Of the few papers which investigated multi-unit sequential auctions (Brendstrup, 2002; Brendstrup and Paarsch, 2006; Jofre-Bonet and Pesendorfer, 2003), bidders are either assumed to have single-unit demand throughout an auction or they can acquire at most one unit in each round. Relaxing the single-unit assumption introduces a number of econometric and computational challenges to the structural modeling of sequential auctions. For example, how to obtain a good estimate of bidders' demand distribution and incorporate it in the characterization of their bidding strategies? We exploit the unique features of the empirical auction environment and formalize bidders' decision-making process in the auctions in a way that their entry decisions only depend on their (multi-unit) demand. By doing so, we avoid the estimation of joint distribution of bidders' valuation and demand without loss of essential properties of these auctions.

Second, we apply our model to a complex B2B market, namely, the Dutch Flower Auctions. Apart from providing rich empirical data for auction research, the Dutch Flower Auctions are economically important: they account for more than 60% of the global flower trade and the annual turnover from these auctions amounts to more than 4 billion Euros. Given such sheer magnitude of transactions processed via these auctions, it is important for the auctioneers, who

act as the market operators, to design and implement the auctions in such a way that they best meet the pre-defined goals, e.g., maximizing the expected revenue. However, due to cognitive and computational limitations, auctioneers cannot sufficiently process the market information and adjust the key auction parameters accordingly to influence the market dynamics under the extreme time pressure in these auctions. To address these challenges, we develop a dynamic optimization approach built on the structural properties of these auctions. The empirical results show that our approach is very promising in guiding auctioneers' decision-making in the complex environment.

Third, our work also contributes to the nascent literature on the design and implementation of smart markets (Bichler et al., 2010). Smart market research aims to develop a comprehensive understanding of the characteristics of complex trading environments and assist human decision makers in these complex environments via the use of various computational tools. Over the past decade, IS researchers have already made extensive progress in the development and deployment of different computational tools (Adomavicius and Gupta, 2005; Adomavicius et al., 2009; Bapna et al., 2003; Ketter et al., 2009, 2012; Mehta and Bhattacharya, 2006). Specifically, researchers have demonstrated that software agents (Wooldridge and Jennings, 1995) have great potential for automating, augmenting and coordinating decision processes in complex environments. In light of this, we propose to use intelligent software agents to facilitate auctioneers' decision-making in the sequential auctions. By learning from the historical transactions as well as the experience of auctioneers, these agents can predict the future auction states and offer well-grounded recommendations to auctioneers to optimize the auctions in real-time.

The rest of this chapter is organized as follows. Section 2 reviews the related literature. Section 3 describes the data and preliminary analysis. Section 4 presents the structural model. In Section 5 we first discuss the estimation results and then conduct policy simulations to assess the performance of alternative auction formats. Further, we also demonstrate how to use structural analysis to dynamically optimize key auction design parameters in sequential auctions. Finally, in Section 6, we draw conclusions and outline the future research directions.

3.2 Literature Review

In this section, we first differentiate our work from the existing work on structural econometric methods in auction research and then review the nascent literature on agent-based decision support.

3.2.1 Structural Econometric Literature

Structural modeling of auction data has emerged as one of the most successful areas of structural econometric research. As opposed to the traditional reduced-form approach in empirical auction research, the structural approach has two important advantages (Hickman et al., 2012): first, it allows for policy counterfactuals of situations not observed from the empirical data; second, by incorporating economic theory, it enables the inferences about allocative efficiency, bidders' risk attitudes as well as other properties regarding information structure.

Over the past two decades, econometricians have developed both parametric (Donald and Paarsch, 1996; Laffont and Vuong, 1995; Paarsch, 1992)) and non-parametric (Flambard and Perrigne, 2006; Guerre et al., 2000) methods for common auction formats within the independent private value paradigm (IPV), and thus provide useful tools for policy analysis. From the methodology perspective, our current work is closely related to the seminal paper on non-parametric estimation by Guerre et al. (2000). However, there are some fundamental differences between the setup in Guerre et al. (2000) and our work. First of all, Guerre et al. (2000) deals with single-object auctions whereas we are studying sequential auctions. Identification and estimation in sequential auctions are much more challenging than in the single-object case -when bidders' private values and strategies are high-dimensional, little is known about the equilibrium characterization (Hickman et al., 2012). In particular, when leaving aside the restrictive assumption that all bidders have single-unit demand, a full treatment of sequential auctions is only possible under very special cases (Brendstrup, 2007; Donald et al., 2006; Katzman, 1999). In our case, the fact that bidders have multi-unit demands at each stage of a sequential auction pushes it even further.

Secondly, Guerre et al. (2000) assumes the number of bidders is known a priori. Although such assumption is quite common in both theoretical and empirical auction literature, in practice, it is rarely the case that the total number of potential bidders is given. Further, if entry to an auction is endogenous - for example, in our case bidders have to purchase no less than the required minimum amount in an auction and this can be considered as an implicit entry bar - the number of active bidders in an sequential auctions becomes stochastic. In light of this, we develop an entry model where bidders receive their signal before deciding whether to enter the current auction and the entry decisions are conditioned on their demands. In this sense, our entry model bears some similarity to the third type of entry models proposed in Li and Zheng (2009), however, the latter focuses on policy issues in single-object procurement auctions whereas we are examining multi-unit sequential auctions.

3.2.2 Agent-based Decision Support

Prior research has shown that software agents offer great promise in assisting humans with their decision-making efforts (Maes, 1994; Wellman et al., 2007; Wooldridge and Jennings, 1995), especially in information-rich and time-critical domains (Ketter et al., 2012). Of particular importance to the current work is Adomavicius et al. (2009) where the authors use the theoretical properties of a given auction mechanism to design strategies for intelligent bidding agents. Using data generated from a simulation model, they demonstrate that these intelligent agents can achieve a higher winning probability while retaining a high surplus for bidders.

Although our work shares the general decision-support spirit of Adomavicius et al. (2009), the two papers differ in several dimensions. For one thing, Adomavicius et al. (2009) has primarily focused on bidders' perspective whereas we are interested in optimizing auctioneers' decisions. For another, Adomavicius et al. (2009) adopts the reduced-form approach to characterize auction process and study price dynamics⁴ while we begin with the identification of the underlying distribution of bidders' valuation using structural econometric approach and then incorporate the derived structural properties into the optimization of key auction parameters.

Finally, unlike most of the existing literature on agent-based decision support where the quality of recommendations from agents are often evaluated on simulated data, we are able to measure the performance of the agents' key capabilities using a rich real-world dataset. Such benchmarking is critical to the applicability of software agents in practice.

3.3 Data and Preliminary Analysis

Our dataset contains the auction details of large roses at a major auction site during May and July, 2011. There are 22 attributes, two of which are the bidders' real-time decision variables: price and quantity. The remaining variables can be classified into seven broad categories: (1) product characteristics (for example, product type, stem length, bundling size, blooming scale, and quality); (2) transaction timing (date and time); (3) supply-side information which includes lot size and minimum purchase quantity; (4) the precise market actors (seller identity and buyer identity); (5) logistics (stems per unit, units per trolley, and number of trolleys); (6) bidding channel (online or offline); (7) clock specification (for example, clock stand and currency unit).

The particular product we chose to study is Avalanche Rose⁵, because its total transaction amount was the largest among the entire assortment, and it was sold steadily throughout the two-

⁴Here, we are not questioning the applicability of the reduced-form approach, since the set-up in Adomavicius et al. (2009), to a large extent, is motivated by online B2C auctions where a variety of behavioral factors come into play.

⁵Avalanche Rose is considered by high class florists, floral designers and demonstrators as an indispensable element in exclusive rose arrangements, displays, bouquets and venue decorations.

month period. In order to rule out potential confounding factors related to flower characteristics in the structural modeling⁶, we created a subsample where the flowers on sale were of the same stem length, bundling size, blooming scale and quality level. This left us with 2754 transactions made by 222 bidders. In total, 31396 units from 189 lots were auctioned over 63 days.

We first examined the price dynamics during the two-month period using a series of boxplots. Figure 3.1 provides an overview of the price trend as well as the daily price variation. We can see that over the three-month period, the winning prices exhibited a fairly consistent pattern: first went up gradually and then fell down again. In addition, the average price exhibited

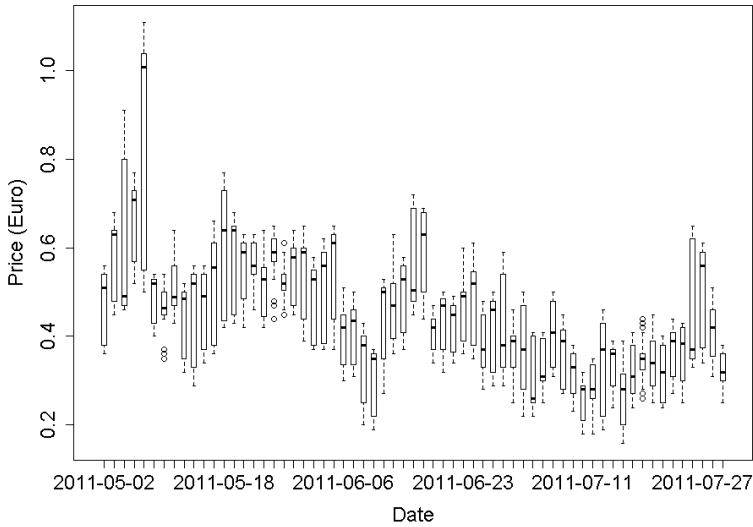


Figure 3.1: Boxplots of daily price variation from 2 May, 2011 to 27 July, 2011.

a clear upward trend right before Mother's Day (May 8th), and the price varied substantially during these peak days, for example, the highest price exceeded 1 euro on May 6 whereas on a regular day the highest price was typically below 80 cent.

A major difference between sequential auctions used in various online B2C auctions and the ones used in the DFA is that bidders can purchase multiple units in each transaction in the latter setting. From the modeling perspective, bidders' purchase quantities serve as good proxy of their demands. Therefore, we also examined the underlying patterns of bidders' purchase quantities.

⁶Flower characteristics have strong influence on bidders' participation in the auctions, in order to obtain a good estimate of the number of potential bidders in the structural modeling, we decided to control the observable product heterogeneity.

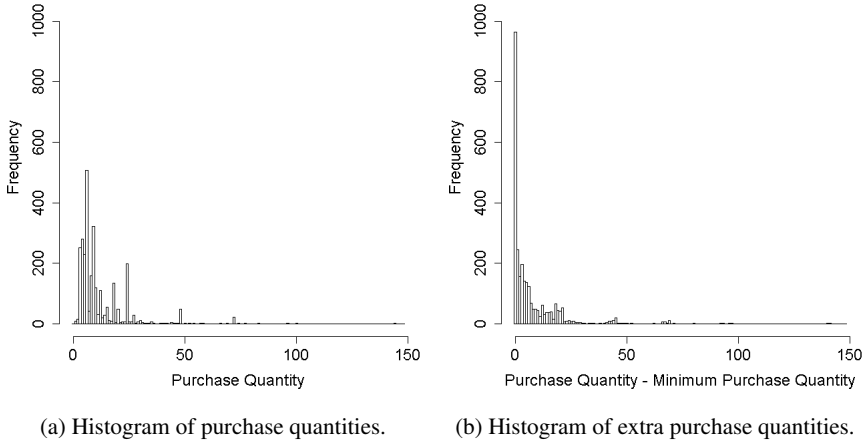


Figure 3.2: Distribution of bidders' purchase quantities and extra purchase quantities, i.e., purchase quantities less the corresponding minimum required purchase amount.

Figure 3.2a shows the histogram of bidders' purchase quantity. We can find that in most cases bidders purchased less than 20 units in each transaction. Further, we plot the distribution of bidders' extra purchase quantities, i.e., purchase quantities subtracted the corresponding minimum required purchase quantities in Figure 3.2b. The enormous amount of zeros suggests that a large portion of bidders only bought the minimum required units. Therefore, it is important for auctioneers to choose the minimum purchase quantity appropriately as the auction proceeds.

Finally, since previous research shows that bidders in sequential online auctions tend to exhibit forward-looking behavior (Zeithammer, 2006), we analyzed the bidding patterns at both auction level and day level. At auction level, we found that repeated bidding (winning) happened in 65 auctions (approximately 18.5% of the total number of auctions) and a total of 35 bidders (approximately 13% of the bidder population under consideration) won multiple times (mostly twice). Anecdotal evidence⁷ suggests that repeated bidding in these auctions is not planned, but a response to new-arriving orders or requests from customers. At day level, we divided the total time⁸ for auctioning the particular flower into 10 sub-slots and plotted the bidding frequency within each sub-slot. It follows from Figure 3.3 that the bidding frequency (normalized) does not differ much across the 10 sub-slots, meaning that bidders did not deliberately postpone their bids towards the end. Given these observations and evidence, we decided

⁷We conducted several interviews with the auctioneers and buyers in 2011.

⁸Although the time stamps for auctioning the particular type of flower under consideration varied, for a given day, the flowers from a given supplier with homogeneous properties were only assigned a single time-slot for auctioning.

to not consider forward-looking in the modeling process.

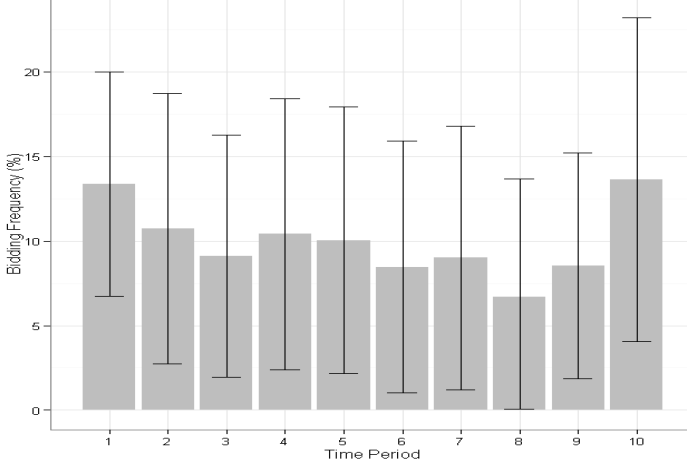


Figure 3.3: Bidding frequency (in percentage) at day-level. The total auction time is divided into 10 sub-slots, and the bidding frequency within each slot is averaged over 63 days.

3.4 Structural Model

In this section, we first formalize the auction process and present the structural model⁹. We then discuss the estimation procedure in detail.

3.4.1 Model Setup

Consider an auction lot consisting of l units. The number of rounds K it takes to reach the end of the auction varies from a minimum of one, when all units are sold via a single transaction, to a theoretical maximum of l , when only one unit is sold via each transaction. In other words, K is endogenous to the auction process. At the beginning of the auction, the clock starts at a price s_1 set by the auctioneer, and ticks down until one bidder stops the clock with a bid b_1 . The winner then chooses the purchase units q_1 . If the lot is not exhausted, i.e., $q_1 < l$, the auction proceeds to the next round with a new starting price, which is equal to the previous winning price plus an increment c . In other words, we have $s_j = b_{j-1} + c$ for $j = 2, \dots, K$. Winning price b_j in the j -th round is always between the starting price and the pre-determined reserve price b_R , and the number of units sold, q_j , varies from zero (when the price drops below b_R) to the total number

⁹A summary of the notations used in the derivation of the model can be found in Appendix A.

of available units at the beginning of the j -th round. Further, at the beginning of each round, the auctioneer determines the minimum purchase quantity m_j and we have $q_j \geq m_j$ except in the last round where occasionally the remaining units can be less than the minimum purchase quantity.

Auctioneer's Decision Problem.

Given an l -unit auction, the auctioneer's key decision variables in the j -th round include: (1) reserve price b_R , (2) starting price s_j , (3) minimum purchase quantity m_j , and (4) clock speed. Currently, the reserve price is set to a negligibly low value which is fixed over the whole year and it has almost no impact on bidders' decisions. The clock speed and the increment c associated with the starting price are also kept constant. Thus in practice, minimum purchase quantity m_j is the only variable that auctioneers can manipulate to influence the bidding dynamics (e.g., the competition level) in a given auction. However, unlike reserve price or clock speed which has been well studied in the auction literature (Katok and Kwasnica, 2008; Levin and Smith, 1996) the effects of minimum purchase quantity is not nearly as well understood. One of the aims of this research is to develop a good understanding about the impact of minimum purchase quantity on bidders' decision-making through structural econometric analysis.

Bidder's Decision Problem.

Bidder i 's decision-making process in round j consists of the following steps: (1) decide whether to participate in the bidding competition, given the minimum purchase quantity m_j ; (2) submit¹⁰ the bid b_j^i , given that he decided to compete in round j ; (3) choose the purchase quantity q_j^i conditional on the fact that he is the winner of the sub-auction in round j .

Suppose there are N ($N > 2$) risk-neutral bidders for the current auction. Within the standard symmetric IPV paradigm, each potential bidder i ($i = 1, \dots, N$) is assumed to have a private value v_i . Bidder i does not know other bidders' private values but knows that all private values including her own have been drawn¹¹ independently from a common distribution F , which is absolutely continuous with density f and support $[\underline{v}, \bar{v}] \subset \mathbb{R}_+$. The equilibrium bid b_i of bidder i is given by:

$$b_i = \mathfrak{s}(v_i, F, N, \underline{v}) = v_i - \frac{\int_{\underline{v}}^{v_i} F(u)^{N-1} du}{F(v_i)^{N-1}}. \quad (3.1)$$

¹⁰All the bidders who are interested in the current round of auction can submit a bid, however, only the first (highest) bid gets revealed and recorded, i.e. we don't observe losing bids.

¹¹Unlike the examples in Paarsch et al. (2006) where bidders are assumed to have decreasing marginal utility in sequential rounds, we do not differentiate a single bidder's valuation towards different number of units. That is, for a given bidder, her unit value of a given product is invariant of her demand. This is because most bidders in these auctions are buying on behalf of their clients and the products sold via these auctions are not for personal consumption but quickly resold to different end markets.

\mathfrak{s} denotes the equilibrium strategy, which is obtained by solving the first-order differential equation¹²:

$$1 = (v_i - \mathfrak{s}(v_i))(N - 1) \frac{f(v_i)}{F(v_i)} \frac{1}{\mathfrak{s}'(v_i)}, \quad (3.2)$$

with boundary condition $\mathfrak{s}(\underline{v}) = \underline{v}$.

The equilibrium relation in Equation 3.1 is the basis of structural analysis of auction data. Specifically, since b_i is a function of v_i , which is randomly drawn from F , b_i is also random, with a distribution that is uniquely determined by Equation 3.1. A fundamental issue in structural estimation is whether the unobserved structural elements (e.g., F) can be identified from the observables (e.g., b_i). In our case, since winning bids are revealed during each round of a sequential auction, according to Athey and Haile (2002), bidders' value distribution F is identifiable.

3.4.2 Estimation of Bidder's Value Distribution

We adopt the nonparametric estimation method proposed by Guerre et al. (2000) to recover the distribution of bidders' valuation from the observed winning bids. The main idea of this method relies on the observation that the first derivative \mathfrak{s}' and the distribution F with its density f can be eliminated simultaneously from Equation 3.2 by introducing the distribution G of b_i and its corresponding density g . Specifically, for any $b \in [\underline{v}, \mathfrak{s}(\bar{v})]$, $G(b) = \Pr(B \leq b) = \Pr(V \leq \mathfrak{s}^{-1}(b)) = F(\mathfrak{s}^{-1}(b)) = F(v)$. Taking the derivative of $G(b)$ and $F(v)$, we have $g(b) = f(v)/\mathfrak{s}'(v)$. Therefore, Equation 3.2 can be rewritten as

$$v_i = b_i + \frac{1}{N - 1} \frac{G(b_i)}{g(b_i)}. \quad (3.3)$$

The nonparametric estimation works in two steps. In the first step, we construct a sample of *pseudo* private values based on the kernel estimates of the distribution and density of observed bids using the relation in Equation 3.3. Then, in the second step, the sample of pseudo values is used to estimate nonparametrically the density and distribution of bidders' private values. This two-step nonparametric method was initially proposed for first-price auctions where all the submitted bids (winning bids as well as losing bids) are available for the estimation. In our case, since only winning bids are revealed, the direct application of the above two-step estimation only gives the distribution and density of the *highest* values of the bidders, which need to be further converted to the value distribution of all bidders using order statistics. A full description of the estimation procedure involving Dutch auctions (i.e., only winning bids

¹²The first-order condition is derived by maximizing the expected profit under the risk neutrality and symmetric assumptions.

are observed) can be found in Paarsch et al. (2006). Below we will provide a sketch of this procedure.

Let G_W denote the cumulative distribution of winning bids. Under the symmetric IPV paradigm, we have $G_W(w) = G(w)^N$. For a random sample of \mathcal{T} observations (denoted by $W_t, t = 1, \dots, \mathcal{T}$) with identical number of bidders, we can estimate¹³ $G_W(w)$ by

$$\tilde{G}_W(w) = \frac{1}{\mathcal{T}} \sum_{t=1}^{\mathcal{T}} \mathbf{1}(W_t \leq w), \quad (3.4)$$

where $\mathbf{1}(\cdot)$ is the indicator function. The corresponding probability density function of winning bids $g_W(w)$ is then estimated by

$$\tilde{g}_W(w) = \frac{1}{\mathcal{T}} \sum_{t=1}^{\mathcal{T}} \frac{1}{h} \kappa\left(\frac{W_t - w}{h}\right), \quad (3.5)$$

where h is a sequence of bandwidth parameters such that h goes to zero and $\mathcal{T}h$ goes to infinity as \mathcal{T} goes to infinity. $\kappa(\cdot)$ is a kernel smoothing function. An important issue with the nonparametric estimation in Equation 3.5 is the trade-off between bias and variances. Here, bandwidth h is similar as the bin width for histograms and it has a strong influence to the estimation results. Following the rule of thumb suggested by Silverman (1986), we choose h equal to $1.06\sigma\mathcal{T}^{-1/5}$ where σ is the standard deviation of winning bids. In practice, we can use the sample standard deviation in lieu of σ .

The valuation of the highest bidder in transaction t can thus be recovered by

$$\tilde{V}_{(1:N)t} = W_t + \frac{N}{N-1} \frac{\tilde{G}_W(W_t)}{\tilde{g}_W(W_t)}. \quad (3.6)$$

Equation 3.6 can then be used to estimate the distribution function of the highest valuation using the following relation:

$$\tilde{F}_Z(z) = \frac{1}{\mathcal{T}} \sum_{t=1}^{\mathcal{T}} \mathbf{1}(\tilde{V}_{(1:N)t} \leq z), \quad (3.7)$$

and bidders' value distribution can be estimated by

$$\tilde{F}(v) = \tilde{F}_Z(v)^{\frac{1}{N}} = \left[\frac{1}{\mathcal{T}} \sum_{t=1}^{\mathcal{T}} \mathbf{1}(\tilde{V}_{(1:N)t} \leq v) \right]^{\frac{1}{N}}. \quad (3.8)$$

So far in our estimation process we have implicitly assumed the number of bidders, N , is known. However, in practice, it is often difficult to determine this number in multi-unit sequential Dutch auctions. For one thing, only winning bids are observed in Dutch auctions. This is

¹³In the following, we use a “ \sim ” atop a letter to denote the corresponding estimate.

fundamentally different from open-cry English auctions or First-price sealed bid auctions. For another, bidders can easily log in or log out with the current bidding system at any point of an on-going auction, and not all the bidders who have logged in to the current auction are truly interested in the products under auction. Instead, some might be collecting market information and preparing for their bidding in the upcoming auctions by logging in earlier than necessary. In the following, we will discuss how to tackle the challenge of the estimation of N .

3.4.3 Estimation of the Number of Bidders

In general, there are two approaches to model the number of bidders in an auction: one considers the number as resulting from an exogenous stochastic process while the other tries to endogenize bidders' entry process. We took the second approach by associating a bidder's participation in a given auction with her demand. To start with, we first give the definition of an *active* bidder.

DEFINITION. A bidder is considered to be active in round j if her unfulfilled demand is equal or larger than the minimum purchase quantity m_j .

Let N_j denote the number of active bidders in round j of an auction. We have

$$\mathbf{E}(N_j|m_j) = \mathbf{E}\left(\sum_{i=1}^{N_{total}} x_{i,j}|m_j\right) \quad (3.9)$$

where N_{total} is the total number of bidders who have logged in to the auction system and $x_{i,j}$ is a binary variable defined as follows:

$$x_{i,j} = \begin{cases} 0 & \text{if } D_j^i < m_j, \\ 1 & \text{if } D_j^i \geq m_j. \end{cases} \quad (3.10)$$

Here, D_j^i stands for Bidder i 's demand in round j . Since most bidders only buy the minimum required units and the empirical distribution of bidders' extra purchase units ($D_j^i - m_j$) is over-dispersed (see Figure 3.2b), $D_j^i - m_j$ is modeled with zero-inflated negative binomial distribution (Wang and Boutilier, 2003; Winkelmann, 2008):

$$f_{ZINB}(D_j^i - m_j) = \begin{cases} \pi_{i,j} + (1 - \pi_{i,j}) \cdot \text{NegBin}(D_j^i - m_j) & \text{if } D_j^i = m_j, \\ (1 - \pi_{i,j}) \cdot \text{NegBin}(D_j^i - m_j) & \text{if } D_j^i > m_j, \end{cases} \quad (3.11)$$

where $\pi_{i,j}$ captures the probability of extra zero counts and NegBin is given by

$$\text{NegBin}(Y = y) = \frac{\Gamma(y + \tau)}{y! \Gamma(\tau)} \left(\frac{\tau}{\lambda + \tau}\right)^\tau \left(\frac{\lambda}{\lambda + \tau}\right)^y, \quad y = 0, 1, \dots; \lambda, \tau > 0. \quad (3.12)$$

$\Gamma(\cdot)$ is the gamma function, τ is a shape parameter which quantifies the amount of over-dispersion, and $\lambda = \mathbf{E}(Y)$, where in our case $Y = D_j^i - m_j$.

Now the only issue left is how to estimate N_{total} , the total number of potential bidders in the auctions. We develop an iterative strategy. The general idea is to start with an educated-guess

of the total number of potential bidders¹⁴ and gradually refine it by minimizing the difference between the distribution of the observed winning bids and the distribution of the *induced* winning bids generated from the current estimate of the total number of potential bidders, using the Kullback-Leibler (KL) divergence (Kullback and Leibler, 1951) measure:

$$\mathbb{D}_{KL}(\tilde{g}_W || \tilde{g}_{induced}) = \int \tilde{g}_W(w) \log \frac{\tilde{g}_W(w)}{\tilde{g}_{induced}(w)} dw. \quad (3.13)$$

We conduct simulations to test the effectiveness of such iterative strategy. The results show that the estimated total number of potential bidders are quite accurate¹⁵.

3.5 Empirical Results

Before presenting the empirical results, we would like to briefly discuss the applicability of the above theoretical framework to the context of the Dutch Flower Auctions. First of all, according to Milgrom and Weber (1982a), the IPV framework suits better than the common value framework in case of nondurable consumer goods such as flowers. In addition, the IPV paradigm can be justified by the market structure: bidders in the DFA are typically serving distinct market segments and they come to the auctions with the willingness-to-pay of their customers. As a matter of fact, most bidders have firm-specific marginal revenue curves, which lead to the variation of their valuations. Next, the risk neutrality assumption is appropriate because most bidders do not face strong budget constraints and if they lose an auction, there are often other lots available on the same day which can serve as close substitutes. Further, the *indifference* assumption regarding bidders' unit value on different amounts is supported by the fact that bidders are mostly buying on order and the products purchased via the auctions are not for personal consumption but quickly resold to different end markets. This is quite different from B2C context where bidders with multi-unit demand in sequential auctions are often assumed to have decreasing marginal utility.

3.5.1 Estimation of Structural Model

Using the transaction data described above, we recovered the distribution of bidders' valuation. The cumulative distribution functions under various minimum purchase quantities are presented in Figure 3.4. Although there seems to be a slightly higher percentage of low-valuation bidders (valuation between 0 and 0.3) when minimum purchase quantity is set to 1, overall, the three estimated distributions are quite similar. In other words, the potential demand heterogeneity does

¹⁴A possible choice can be the average number of winning bidders for the given flower on a daily basis.

¹⁵The details of the simulation-based test can be found in Appendix B.

not seem to lead to considerable differences in bidders' value distribution. This also suggests that the way we used to model bidders' decision-making process is appropriate.

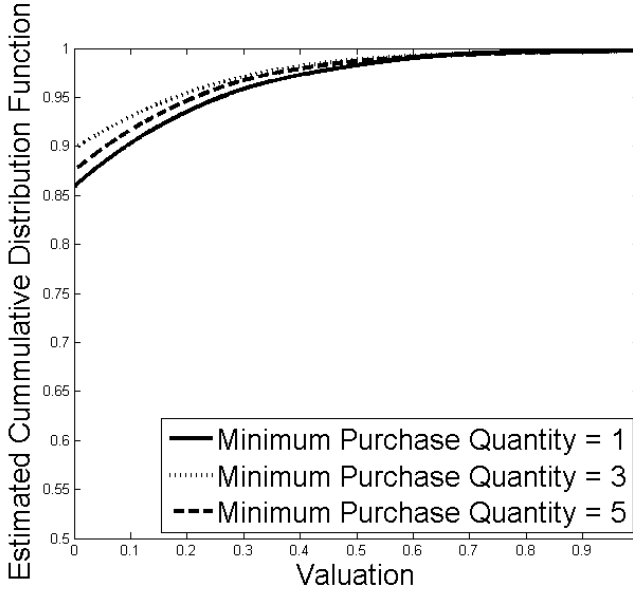


Figure 3.4: Estimated distribution functions of bidders' valuations on Avalanche Rose.

Another important observation from Figure 3.4 is that a large percentage of logged-in bidders' valuation is below zero, meaning they are not truly interested in the current (sub) auctions they have logged in to. This is consistent with the anecdotal evidence we have acquired from the onsite interviews at the flower auctions as well as the previous findings by Van den Berg and van der Klaauw (2007) - while the average number of bidders registered during an auction was around 50, only 5-7 bidders were actually participating in the bidding.

We also compared the estimated bid functions under different required minimum purchase units. The results can be seen from Figure 3.5. Here, the main observations are: 1) bidders shade their bids considerably below their valuations in all three cases; 2) bidders with higher valuations shade more than low valuation bidders; 3) bidders tend to bid more aggressively when minimum purchase quantity is set to one. A possible explanation to the expected bid increase under low minimum purchase quantity is that bidders would face tougher competition and higher uncertainty on future supply (Jeitschko, 1998), since a low minimum purchase quantity attracts more bidders to participate in the bidding and opens more possibilities.

By explicitly recovering the distribution of bidders' valuations and bid functions, we can simulate auction results under alternative auction designs and compare the performance of dif-

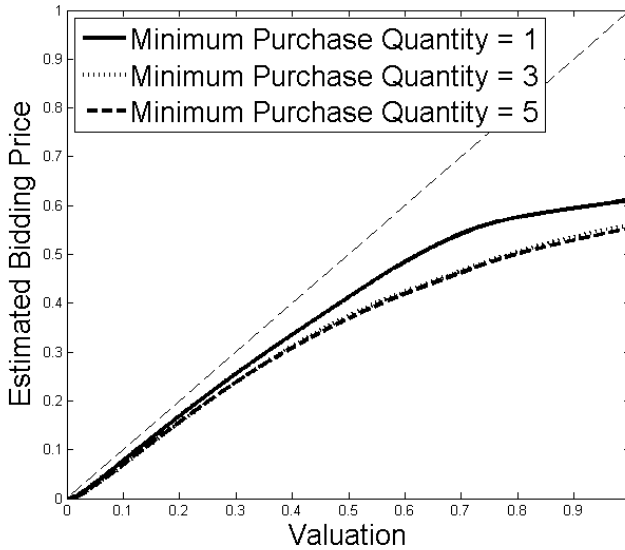


Figure 3.5: Estimated bidding functions.

ferent designs. In the following, we will discuss the policy simulation on different choices of minimum purchase quantities.

3.5.2 Robustness Check

One of the main concerns when applying the structural estimation to empirical context is that bidders tend to deviate from the equilibrium strategies (see Ariely and Simonson (2003) for example) thus the implications from the estimation results might be misleading. In order to investigate the impact of potential behavioral “noises”, we re-run the structural estimation by introducing measurement errors in the data generating process.

In particular, we posit that the observed winning bids consists of two parts which are independent from each other: the expected *willingness-to-pay* which is determined by the bidding strategy and a bidder’s value, and the error term¹⁶. Thus for a random sample of \mathcal{T} observations W_t , ($t = 1, \dots, \mathcal{T}$), we have

$$W_t = B_t + \varepsilon_t(R_t), \quad t = 1, \dots, \mathcal{T}, \quad (3.14)$$

where B_t denotes the *expected* or *planned* bid and $\varepsilon_t(R_t)$ is the error term which captures the

¹⁶The independent assumption is used as a standard condition in most of the additive error models

aggregated effect of unobserved behavioral factors. We allow for heteroscedastic contamination in Equation 3.14, i.e., each error term can have its own density function.

Let $f_W(\cdot)$ denotes the density of observed winning bids (contaminated with behavioral noises), $g(\cdot)$ the density of expected bids, and $f_R(\cdot)$ the density of error term. Under the independence assumption,

$$f_W(w) = \int g(b)f_R(w - b)db. \quad (3.15)$$

The estimation of $g(\cdot)$ without imposing any parametric assumption is often referred as *deconvolution* problem (Krasnokutskaya, 2011). In general, when f_W and f_R are known, $g(\cdot)$ can be recovered by Fourier inversion¹⁷.

To test the robustness of the structural estimation results in Section 3.5.1, we conduct simulation experiment where we assume the error term follows normal distribution, i.e.,

$$\varepsilon(R_t) \sim \mathcal{N}(0, [0.01\sigma * (0.5 + R_t/\max(R_t))]^2). \quad (3.16)$$

Here σ controls the magnitude of the noises. Since in the current system it takes 36 milliseconds for the clock to go down by 1 tick and the average human reaction time is around 200 milliseconds, we set $\sigma = 1, 2, 3, 4, 5$ in the experiment. Further, in order to deal with the heteroscedasticity in the errors, we use the kernel density estimator proposed by Delaigle and Meister (2008) to recover the density function of expected (planned) bids before proceeding to the structural estimation procedure described in Section 3.4.2. The final estimation results can be seen in Figure 3.6.

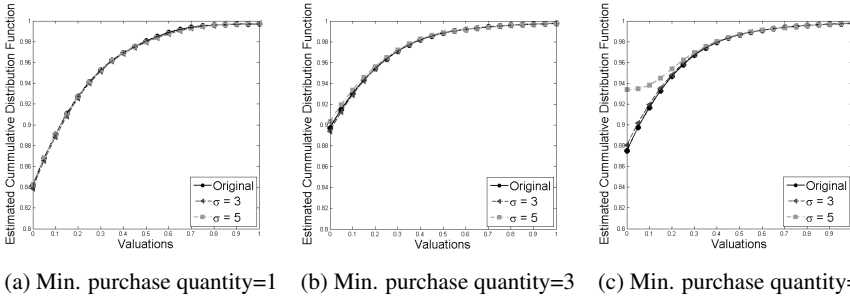


Figure 3.6: Estimated value distribution functions when considering behavioral noises in the bidding process.

We can find that when minimum purchase quantity is set low (e.g., 1 or 3), the estimated value distribution is quite robust to behavioral noises. In fact, according to Figure 3.6a and

¹⁷For details of the derivation, see Appendix C.

Figure 3.6b, the estimated value distributions for the cases when we introduce behavioral noises in the bidding process are almost the same as the original one when we do not consider errors in the data generating process. On the other hand, when the minimum purchase quantity is increased to 5, which means the number of active bidders for the current auction is decreased, the estimated distributions are quite different under the purely rational setting where bidders follow equilibrium strategy and the highly noisy setting where bidders considerably deviate from the equilibrium strategy (e.g., $\sigma = 5$). In fact, we might overestimate the percentage of low-value bidders by almost 6%.

Overall, the simulation test shows that the results from our structural estimation is quite robust against behavioral noises, i.e., even if bidders are not strictly following the equilibrium strategy and the observed winning bids are contaminated by some unobserved factors, the estimated value distribution is still reliable. However, when the bidding process is subject to significant shocks, the estimation results might be problematic. A full treatment of this issue is out of the scope of this paper and we shall leave it as future work.

3.5.3 Policy Simulation

As we have already seen, minimum purchase quantity has a strong impact on the bidding dynamics. On one hand, bidders use the specific minimum purchase quantity in each round as an external reference point when determining their purchase quantities, and they are inclined to purchase the exact amount of minimum required units. Thus increasing minimum purchase quantity is often considered to be an effective way to speed up the auction process. On the other hand, a large minimum purchase quantity might deter potential bidders' entry to an auction and thus leads to less competition and low price. Currently, auctioneers mainly rely on their intuition and experience to decide the minimum purchase quantity in each round. Typically, they set a relatively low minimum purchase quantity at the beginning and gradually increase it as the auction proceeds. Empirically, it is important to find out whether such *rule-of-thumb* yields desirable outcomes.

With the estimated value distribution, we can simulate auction results under different designs. Therefore, we compared the expected total revenue and market clearing speed, which is measured by the number of rounds needed to finish the given auctions, of two alternative designs where the minimum purchase quantities are set in different ways – 1) fixed design where the minimum purchase quantity is always set to 1; 2) heuristic design where the minimum purchase quantity is monotonically increasing as 1, 1, 2, 2, ..., and so on – with the observed design (benchmark). For each of the alternative designs, we first simulated bidders' private values and demands from the estimated distributions. For a given minimum purchase quantity, we then used the estimated bidding function to generate the winning bid and purchase quantity. Such

simulation process is repeated for 50 times. The mean and standard deviation of total revenue and number of rounds corresponding to each design are summarized in Table 3.1.

Table 3.1: Comparison of the performance of different auction designs.

	Total Revenue (in Euro)		Number of Rounds	
	Mean	Std.	Mean	Std.
Observed Design (Benchmark)	589,231	-	2,754	-
Fixed Design	737,471	2,637	3,605	144
Heuristic Design	624,909	2,465	2,682	21

According to Table 3.1, the observed design is neither best in terms of maximizing total revenue nor increasing market-clearing speed. The fixed design outperforms the observed design substantially in terms of revenue maximization: the expected total revenues from both designs are 25 percent higher than the observed design. However, such improvement comes at an extremely high cost in terms of market clearing speed: the expected number of rounds taken to finish the auctions increased by 31 percent. Given the tight daily auction schedule and high operation costs, such extended auction time is not acceptable. On the other hand, the heuristic design indeed shows improvement on market-clearing speed: the expected number of rounds taken to finish the auctions reduces by approximately 3 percent. Further, to our surprise, the expected total revenue from the heuristic design is 6 percent higher than the observed design¹⁸. This suggests that there is ample room to improve the way of setting minimum purchase quantities in the sequential rounds.

3.5.4 Dynamic Optimization of Key Auction Parameters

Due to cognitive and computational limitations, auctioneers cannot process all the information in the market fast enough to make informed decisions on the key auction parameters. A promising way to address these limitations is to augment auctioneers' capabilities with high-performance decision support tools in the form of software agents (Wooldridge and Jennings, 1995). In order to provide effective decision support, these agents shall be able to: (i) make good predictions of future auction states (e.g., the winning prices and purchase quantities in the upcoming auctions as well as the market trends); and (ii) optimizing the key auction parameters based on the predictions. In the following, we will discuss how to apply the structural analysis in the dynamic prediction and optimization of key auction parameters, using the example of minimum purchase quantity.

¹⁸The t-test shows that the difference is significant (p-value < 0.001).

Structural-based Prediction.

In general, two different approaches have been used in prediction tasks arising from auctions: the reduced-form approach and the structural-based approach. The reduced-form approach aims to characterize bidding dynamics and winning prices using a set of observable variables and the main advantage of this approach is that it can effectively adapt the prediction to the market dynamics. The structural approach, on the other hand, attempts to map the observed bids to bidder's valuation and then use the equilibrium bid functions to make predictions. Therefore, it has the advantage of being able to predict the effect of policy changes (e.g., adjustments of minimum purchase quantities). Further, since the structural-based approach can provide normative insights into the auction process itself, the predictions often have better interpretations. However, a key question associated with the structural-based prediction is: how to ensure that the estimated valuation distribution is relevant to the upcoming auctions?

We propose to take a middle path which combines the strengths of the pure reduced-form approach and the pure structural approach by using the most relevant transaction data to estimate the current distribution of bidders' valuations. This means that the pool of training data shall be updated continuously such that the latest transaction data is added while the earliest transaction data is discarded. Further, transactions included in the pool shall be weighted in a way that reflects their relative importance, that is, the more recent the transaction is, the higher weight it gets. This is because the recent transactions are usually more informative in reflecting market trend, especially during highly volatile period. Figure 3.7 provides an illustration of the dynamic training pool where the darker shaded areas indicate transactions with higher weights.

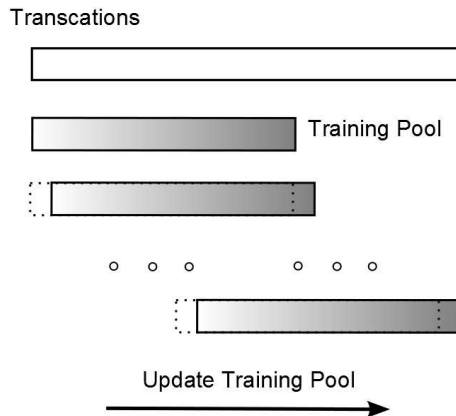


Figure 3.7: A schematic representation of the dynamic training pool. Each instance in the training set is weighted exponentially with respect to its recency.

In order to test the performance of our prediction method, we split the original dataset into two parts: the first $2/3$ transactions as the initial training set and the rest $1/3$ transactions as the test set. The training data is used to recover the distribution of bidders' valuation and predict winning prices in the upcoming auctions. After obtaining the predicted winning price in the upcoming transaction, the true observation of this transaction will be added to the training pool while the earliest observation from the training pool is removed. Therefore, the total amount of transactions used for prediction is constant during the whole procedure. The transactions in the training pool are weighted exponentially according to their recency.

We compared the observed distribution of winning bids on the test set with the estimations from the above dynamic prediction method and static method where the prediction is solely based on the original $2/3$ transaction data. It follows from Figure 3.8 that although both the static and dynamic prediction methods somehow overestimate the proportion of low winning bid between 0 and 0.2, the estimated distribution resulting from the dynamic prediction method shows better fit with the observed distribution. We also performed Kolmogorov-Smirnov test (K-S test) to compare the two estimated distributions and the empirical distribution. For the static model, the resulting p-value is less than 0.01, suggesting the estimated distribution from static model is significantly different from the observed distribution. On the contrary, for the dynamic model, p-value from the K-S test is larger than 0.1. Thus we can conclude that the structural-based dynamic method yields quite accurate prediction.

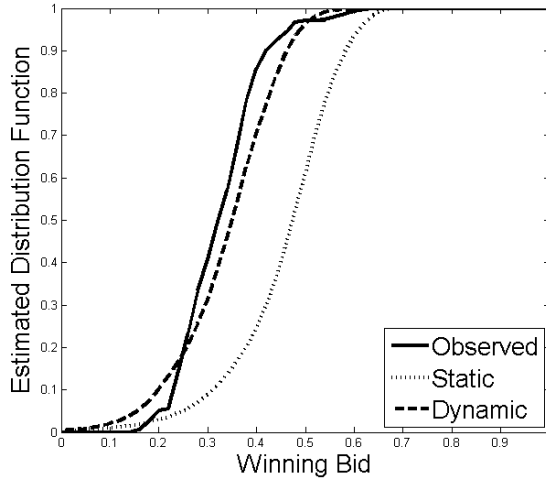


Figure 3.8: The distributions of observed winning prices and predicted winning prices on the test data.

Optimization by Dynamic Programming.

We use dynamic programming to determine the optimal minimum purchase quantities in the sequential rounds. Dynamic programming (Bellman, 1957) refers to a useful algorithmic paradigm where a complicated problem is solved by breaking it down into a collection of simpler sub-problems recursively and tackling them one by one. It ensures the global optimality of the solution and allows for hard constraints to be imposed in a natural and straightforward structure. In our case, the auctioneers' problem is formulated as:

$$\arg \max_{m_j} \mathbf{E} \left(\sum_{j=1}^K B_j Q_j - \phi(K) | m_j \right), \quad (3.17a)$$

$$\text{Subject to } \sum_{j=1}^K Q_j \leq L, \quad (3.17b)$$

$$\forall j \in \{1, \dots, K\}, \quad Q_j \geq m_j. \quad (3.17c)$$

Here, $\phi(K)$ is the penalty function depending on the total number of rounds. Although we do not know the exact operational cost associated with the duration of an auction or total number of rounds taken, the fixed cost bidders need to pay for each transaction¹⁹ can be considered as a type of compensation for the marginal operational cost per round. Therefore, we use a linear model to characterize the penalty term in Equation 3.17a, that is, $\phi(K) = \varphi \cdot K$ and we experiment with different choices of φ . Further, since the minimum purchase quantity in the previous rounds can influence both the winning bid and purchase quantity in the current round, we choose *backward induction* (Adda and Cooper, 2002; Puterman, 2009) to solve the optimization problem defined by Equation 3.17a-3.17c.

Using the same simulation procedure as in the study of policy counterfactuals, we compared the performance of optimized designs (under different penalty settings) with the observed design on the test set. It follows from Table 3.2 that the optimized design without penalty yields considerably higher revenue, although such improvement comes at a high cost of market clearing speed. Such observation is consistent with the results in Table. On the other hand, if the penalty term is set appropriately, the dynamic optimization can lead to significant improvement on the expected revenue at a negligible cost of market clearing speed. For example in our case, when φ is set to 2, the expected revenue increases by 12 percent whereas the number of rounds needed for the given auctions almost stays the same.

In addition, since the auctions operate at a high speed (i.e., each transaction takes 3 to 5 seconds), the optimization of minimum purchase quantities must be completed efficiently or

¹⁹During our interview at a major auction site, we have learned from the auctioneers that bidders need to pay a fixed cost for each transaction, unless she bought the total available amount or a whole trolley of products.

Table 3.2: Comparison of performance between the observed design and optimized designs.

	Total Revenue (in Euro)		Number of Rounds	
	Mean	Std.	Mean	Std.
Observed Design (Benchmark)	180,387	-	1,053	-
Optimized Design ($\varphi = 0$)	211,017	2,441	1,204	36
Optimized Design ($\varphi = 1$)	210,367	1,771	1,160	24
Optimized Design ($\varphi = 2$)	202,805	2,816	1,094	28
Optimized Design ($\varphi = 3$)	170,649	2,803	919	16

even in real-time. Fortunately, during our simulation experiment, we found that the average calculation time for the minimum purchase quantity in the upcoming round is approximately .5 seconds²⁰. This suggests that our proposed optimization approach is indeed applicable to the real-world auctions.

Finally, we would like to point out that our optimization approach is also very *flexible*. For example, auctioneers can leverage their experience to tailor the choices of penalty function to the specific market conditions or market regimes (Ketter et al., 2012). This, however, imposes extra requirements to the software agents - they shall be able to communicate with the users in an effective and efficient manner, or learn about the users' preferences and requirements in a non-intrusive way (Bichler et al., 2010). A full treatment of these design issues is beyond the scope of this paper, and we will leave it to future work.

3.6 Conclusion

We developed a structural model for multi-unit sequential Dutch auctions in a complex B2B context where auctioning and bidding decisions have to be made within a few seconds. To the best of our knowledge, this is the first paper that explicitly models the sequential aspects of these complex auctions using structural analysis. Further, we used the structural model to study policy counterfactuals and evaluate the performance of alternative auction designs. Previous studies have shown that bidders in real-world auctions often exhibit unexpected behavior and deviate from the theoretical prediction. Although a deep understanding of the behavioral aspects in the competitive bidding process will require much more empirical work, the findings from our current research provide a normative benchmark against which alternative designs can be assessed appropriately.

From the managerial perspective, our research provides valuable insights to the practitioners, especially the auctioneers, in their decision-making concerning the key auction parameters.

²⁰The simulations were run on an Intel i5, 2.5 GHz machine with 4G of RAM and Windows 2007.

As Klemperer (1999) pointed out, “auction design is not one size fits all.” In the case of the Dutch Flower Auctions, we have shown that choices of minimum purchase quantities must be tailored to the local circumstances, especially the current market conditions. For example, in order to push more products to the market on peak days such as Valentine’s Day, auctioneers must speed up the auction process by increasing the penalty associated with the expected number of transactions when determining the optimal minimum purchase quantities. Although this might result in a decrease of average revenue per auction, the total revenue can still be increased due to the accommodation of more auctions in the daily auction schedule. Given the cognitive and computational limitations of human decision makers, we propose to augment auctioneers’ capabilities by deploying software agents. These agents can assist auctioneers in optimizing the key auction parameters under different market conditions.

As the next step, we intend to extend our model by taking into account bidder asymmetry in the auctions. Bidder asymmetries arise for different reasons. For example, even bidders’ valuations are drawn from the same distribution, they might have different preferences or risk attitudes. Additionally, in sequential auctions, bidders’ subsequent valuations might also be influenced by the number of units they have won in the past²¹. Note that structural econometric analysis becomes much more challenging when we remove the symmetric assumption, because the system of first-order differential equations that characterizes a Bayesian Nash equilibrium often does not have a closed-form solution and we can only obtain approximate solutions numerically. In order to address these challenges, currently, we are working closely with the auctioneers to better characterize bidders’ valuations. We are also experimenting with different numerical methods and conduct realistic simulations.

²¹In our case, fortunately, bidders are often purchasing on behalf of their clients and they tend to have much stronger sense of valuation as well as willingness to pay. Hence the valuation during the sequential rounds is less likely to vary a lot.

3.A List of Notations

Table 3.3: Summary of notations used in the model

Notation	Explanation
l	The units of products under auctions
K	The number of rounds taken to reach the end of an auction
s_j	The starting price in round j
b_R	The reserve price
c	The constant incremental added on top of the current-round winning price
m_j	The required minimum purchase quantity in round j
N	Number of bidders
F	The cumulative distribution function of bidders' valuation
f	The density function of bidders' valuation
f_W	The density function of observed bids contaminated with behavioral noises
f_Z	The density function of the highest valuation
v_i	Bidder i 's valuation (independently drawn from the unknown value distribution F)
\mathbf{s}	The equilibrium strategy
b_i	Bidder i 's bidding price which depends on v_i , N and F
q_i^j	Bidder i 's purchase quantity in round j .
D_j^i	Bidder i 's demand in round j
$x_{i,j}$	Binary variable which indicates whether Bidder i is active in round j
G	The cumulative distribution function without contamination of behavioral noises
g	The density function of observed bids without contamination of behavioral noises
W_t	Observation in a random sample of winning bids

3.B Simulation-based Test for the Iterative Method

Assuming bidders' private values are drawn from a truncated log-normal distribution with $\mu = -10$ and $\sigma = 5$, the required minimum purchase quantities with a Poisson distribution where $\mu = 4$ and bidders' extra purchase quantities are characterized by the zero-inflated negative binomial distribution with $\pi = 1/3$, $\lambda = 1/9$, $\tau = 1$.

In each simulation, we generate 10 auctions, each with 50 units of a homogeneous product. The bidder with the highest bid²² wins the auction and her demand will be fulfilled. This procedure continues until all the units in the current auction are sold out, and then we move to the next auction. If the remaining units in the current auction are less than the demanded units of the winner, the winner takes all the remaining units and will participate in the next auction.

²²Here we assume all the bidders adopt the equilibrium strategy.

We tested the estimation result from the iterative method for different number of potential bidders. The results are shown in Table 3.4. We can see that

Table 3.4: Results of the simulation-based test.

Actual Number of Potential Bidders	Estimated Number of Potential Bidders	
	Mean	Standard Deviation
60	72.15	5.85
70	77.45	5.91
80	82.55	5.61
90	87.40	2.66
100	93.85	3.84
110	102.80	3.58

3.C The Deconvolution Problem

For each random variable X , let $\psi_X(t)$ denote its characteristic function, i.e.,

$$\mathbf{E}(e^{itX}) = \int e^{itx} f_X(x) dx. \quad (3.18)$$

According to Equation 3.15, we have

$$\psi_W(t) = \psi_B(t) \cdot \psi_\varepsilon(t). \quad (3.19)$$

Thus $\psi_B(t)$ can be derived as a function of series of $\psi_W(t)$ and $\psi_\varepsilon(t)$, and $g(b)$ can be obtained by applying Fourier inversion to $\psi_B(t)$, i.e.,

$$g(b) = \frac{1}{2\pi} \int e^{-itb} \psi_B(t) dt. \quad (3.20)$$

Chapter 4

Exploring Bidder Heterogeneity in Sequential B2B Auctions¹

4.1 Introduction

The proliferation of online auctions has offered researchers fertile ground to examine practical auction design and real-life bidding behavior (Ariely and Simonson, 2003; Ba and Pavlou, 2002; Bapna et al., 2004, 2009; Goes et al., 2010; Kauffman and Wood, 2006). Most of the work is, however, restricted to auction-level outcomes in the business-to-consumer (B2C) sector, characterized by relatively well-understood products such as electronic devices. Comparatively, little attention has been paid to business-to-business (B2B) auctions which are economically more significant.

Despite the price discovery nature, there are some key features of B2B auctions that are different from those of B2C auctions. First, firms typically only engage in exchange activities with a limited number of partners in B2B markets (Bakos and Brynjolfsson, 1993). As the result, transactions in B2B markets often involve high-level mutual trust and detailed product and quality requirements. For example, in B2B procurement auctions, buyers often adopt a pre-screening process to select the qualified suppliers which will later compete in the bidding process. Second, bidders in the B2B markets are much more knowledgeable and experienced. They often participate in these auctions repeatedly over a long period of time and thus know more about their competitors and the goods they are bidding on. Further, since the vast majority of goods auctioned in B2B markets are not for bidders' personal consumption, they also have

¹This chapter is based on the conference paper "Exploring Bidder Heterogeneity in B2B Auctions: Evidence from the Dutch Flower Auctions", co-authored with Alok Gupta, Wolfgang Ketter and Eric van Heck, and is currently under review at a top-ranked journal in information systems. The author of this dissertation is the first author of these papers. We thank the seminar participants at Carlson School of Management, Rotterdam School of Management, at the Conference on Information Systems and Technology (CIST 2012), and at the Statistical Challenges in eCommerce Research Symposium (SCECR 2012) for feedback and discussions. The authors acknowledge the comprehensive support from FloraHolland.

different incentives as compared to the participants in B2C auctions and thus may pursue different strategies. Third, bidders in B2B auctions are often subject to different levels of budget constraints (Benoit and Krishna, 2001). To better understand and operationalize the differences between B2B auctions and those well-studied B2C auctions, Mithas and Jones (2007) suggest that: “Future research should develop typologies of bidder heterogeneity in the B2B context similar to those that Bapna et al. (2004) developed in the B2C context.”

Using the world’s largest flower wholesale auction market, namely, the Dutch Flower Auctions (DFA) as the research context, this paper addresses the following research questions:

- What bidding strategies do bidders pursue in B2B markets? Are they similar to the strategies found in B2C markets?
- Can bidders’ choices of bidding strategies be explained by their business constraints such as budget and demand as well as their bidding channels?
- How do different bidding strategies affect buyers’ economic welfare?
- How can we use the findings to improve the design of B2B markets?

Unlike those well-studied online B2C auctions which predominantly use either the English auction mechanism or its variation, the DFA uses the Dutch auction mechanism. This means only the winning bids are revealed. Further, these auctions clear very fast - on average, each transaction takes four seconds. Given the sheer magnitude and the extreme time pressure, bidding in the DFA is highly challenging even for professional bidders.

Drawing on a unique and extensive data set that contains more than 250,000 transactions from the DFA, we create four classification variables, three at day-level and one at auction-level to characterize bidders’ bidding strategies. The use of day level variables is a novel contribution to the characterization of bidding strategies in B2B markets. Further, since we can track the identity of bidders over an extended period of time, we also develop an empirical model to explain bidders’ choices of bidding strategies.

Overall, we find a stable taxonomy which consists of five types of bidding strategies. The choices of these strategies are associated with bidders’ business profile as well as their demand and channel adoption and usage. Specifically, our results show that bidders with a high budget are more likely to adopt opportunistic strategy and bid later in an auction. We also find that bidders with a large demand (e.g., wholesalers) are more likely to adopt a participator strategy and actively bidding in the auctions throughout a day. In terms of channel usage, our results show that bidders using the online channel are more likely to adopt participator and opportunistic strategy rather than evaluator strategy at auction-level, in other words, these online bidders tend to wait longer in an auction for a good bargain.

Further, we use a hierarchical linear model to analyze the economic welfare of the identified bidding strategies. The main finding is that opportunistic strategies perform better than both participator strategies and evaluator strategies in minimizing the purchasing cost. This result is different from previous findings in B2C context. Additionally, we also find significant moderating effect of bidding strategies on the impact of auction design parameters. These findings complement previous studies that have focused on B2C context.

This paper makes several important contributions. It is among the first to characterize the bidding strategies pursued by professional bidders in B2B markets. While prior research in B2C context posits that bidders' bidding strategies converge as they gain experience, we demonstrate that despite bidders' extensive experiences, there are theoretically meaningful and empirically robust clusters of bidding strategies in B2B markets. Using an explanatory model, we map the identified strategies to bidders' business profiles, demand and their channel usage. This helps us to better understand the observed differences in bidding strategies between B2C and B2B markets. Further, we investigate a single market where electronic (online) and traditional (offline) channels coexist. This is different from the majority of studies that examines bidders' bidding strategies or channel usage. Finally, given the extreme time pressure faced by the bidders in our empirical context, our findings also sheds new light on real-time decision-making in complex environment. From the managerial perspective, this paper provides useful implications for the microstructure design of B2B auction markets. In particular, our finding that bidders tend to postpone their bidding in the online channel suggests that in order to improve the total revenue and market clearing speed, auctioneers should strategically disclose and tailor the information available to bidders in different channels.

The rest of this chapter is structured as follows. Section 2 provides a review of the relevant literature. Section 3 describes the identification of bidding strategies. Section 4 further examines bidders' choices of strategies and analyzes the outcomes of different strategies. Section 5 discusses the implications of our findings and concludes with a summary of contributions and outlines the future work.

4.2 Prior Literature

In this section, we discuss two streams of literature that are closely related to the current study.

4.2.1 Bidder Heterogeneity

Traditionally, auctions have been studied largely from the game-theoretic perspective. Bidders are assumed to be homogeneous who adopt Bayesian-Nash equilibrium strategy (McAfee and McMillan, 1987; Milgrom, 1989; Myerson, 1981). While plausible in traditional face-to-face

auctions, such assumption quickly breaks down in online context (Ariely and Simonson, 2003; Bajari and Hortaçsu, 2004). This highlights the necessity of studies addressing the gap between the behavioral reality and the predictions from classical theory.

Over the past decades, some researchers have pursued more accurate models to explain the real-life bidding behavior. For example, Carare and Rothkopf (2005) developed theoretical models of the effect of transaction costs on the winning bids in Dutch auctions. Park and Bradlow (2005) incorporated four key components of the bidding process (whether people bid at an auction, who bid, when they bid and how much they bid in the auction) in their integrated model for the bidding behavior in an online auction of notebooks. Others have adopted a data-driven, inductive approach to "understand why real bidders do the things that they do" (Engelbrecht-Wiggans, 2000). For example, using a rich data set from Yankee auctions, Bapna et al. (2004) identified five types of bidding strategies which are associated with different winning likelihoods and consumer surplus. The authors also demonstrated how to use such bidder taxonomy to guide the development of user-centric bidding agents and facilitate real-time auction calibration. More recently, Goes et al. (2012) extended the research on bidder taxonomy to sequential auctions where bidders have the opportunity to participate in multiple auctions and thus to learn from past experience. They found that bidders' choices of bidding strategies are contingent on their demand, participation experience and auction design parameters.

Currently, most of the empirical work on bidder behavior is exclusively focused on B2C auctions. Note that the vast majority of transactions in B2C domain are associated with purchases for personal consumption, which often involve questionable assessment of valuation and, thereby, willingness-to-pay. Additionally, bidders' participation experience in these auctions can vary a lot. Thus a natural question is whether the observed heterogeneity in the B2C auctions will disappear when bidders have a strong sense of willingness-to-pay and have gained sufficient experience, or in other words, whether bidders' strategies will converge if they repeatedly participate in these auctions. Besides its theoretical importance, the answer to this question has also practical implications to auction design.

In this study, we draw upon a unique B2B context where professional bidders compete in multiple sequential auctions repeatedly on a daily basis. Compared to the participants in B2C auctions, these bidders are much more knowledgeable and experienced. Therefore, examining their bidding patterns can help us to better understand the discrepancy between the observed real-life bidding behavior and the predicted behavior in auction theory.

4.2.2 Market Channels

The increasing use of the Internet has fueled the adoption of online (electronic) channels in many markets (Kambil and van Heck, 1998; Kuruzovich et al., 2008; Overby and Jap, 2009).

Compared to traditional offline channels, the online channels offer many benefits to both buyers and sellers. For buyers, they can significantly reduce search costs (Bakos, 1997) and switching costs (Devaraj et al., 2006). For sellers, they greatly increase the market reach and reduce the transaction cost (Kambil and van Heck, 1998).

Despite these advantages, however, the inherent information asymmetry between buyers and sellers in the online channels may result in undesirable outcomes. For example, Dewan and Hsu (2004) find a significant adverse selection discount, i.e., roughly 10-15% of the value of the goods, on eBay. In a more recent study, Ghose (2009) empirically shows that the information asymmetry problem persists in online markets despite the presence of signaling mechanisms such as reputation systems and product condition disclosures.

Given such trade-off, researchers have studied multiple factors that may influence buyer and seller's channel choice – i.e., whether to use online, offline, or multiple channels. Using an extensive panel data that consists of sales event of used vehicles for over a 2.5-year period, Overby and Jap (2009) find that transactions involving low quality uncertainty are more likely to occur in the online channels, whereas those involving high quality uncertainty occur more in the traditional offline channels. As opposed to earlier work, they also examine the interdependencies between buyers and sellers in the market and illustrate that one party's use of online channels influences the other.

In the current study, we do not look into bidders' choices of participation channel in the particular B2B auction market. Instead, we focus on bidders' behavioral characteristics across different channels, e.g., whether bidders who participate in the auctions via the online channel are more likely to adopt certain strategies. A comprehensive understanding of bidding strategies across different market channels is critical to the development of effective information revelation policies (Arora et al., 2007) in multi-channel markets.

4.3 Identification of Bidding Strategies

In this section, we begin with a description of the general characteristics of the data set. We then discuss the classification method and the empirical findings.

4.3.1 Data

Our data set contains transaction details of roses from June 1 to September 30, 2010 at a major auction site where screen (image) auctioning has been implemented. This means, bidders are not shown the actual flowers during the auctions (even they are physically present in the auction hall); instead, they observe a generic picture for that type of flower together with some specific product characteristics of that particular lot below the auction clock. Prior research has shown

that the use of screen auctioning leads to lower prices due to the reduced product quality information (Koppius et al., 2004). However, since both the online and offline bidders receive the same product information, the effect of screen auctioning is not relevant in our study.

In total, we have 280,945 transactions from 38,848 lots². 593 bidders participated in these auctions, of which 288 bidders have adopted the online channel. In order to control for the pre-screening effects related to product category or quality, we created a sub-sample where the products were homogeneous with respect to their key characteristics. The particular product we chose is Avalanche Rose, because its total transaction amount was the largest among the entire assortment, and it was sold steadily throughout the four months. After the sanity check³, we are left with a total of 8384 transactions from 998 auctions. The number of bidders participated in these auctions also reduces from the original 593 to 455. Nevertheless, the new data set is still rich enough for us to explore the bidding strategies pursued in these complex, sequential auctions. Table 4.1 provides a summary of the descriptive statistics. We can see that there is high variability in lot size, winning price and purchase quantity.

Table 4.1: Summary statistics of the sub-sample.

Statistic	Number of Auctions per Day	Bidders per Auction	Number of Auctions a Bidder Participates per Day	Lot Size	Winning Price (cent)	Purchase Quantity
Mean	11.34	8.26	1.24	80.85	36.69	9.62
Median	11.00	7.00	1.00	72.00	37.00	6.00
Standard Deviation	1.99	5.72	0.54	59.95	13.39	13.94
Skewness	0.62	0.79	2.64	1.33	0.15	6.69
Minimum	8.00	1.00	1.00	5.00	7.00	1.00
Maximum	18.00	34.00	6.00	342.00	75.00	311.00

We also examined the price dynamics during the four-month period using a series of box-plots. Figure 4.1 illustrates the daily price variation as well as the price trend. Despite the homogeneity of the auctioned products, the transaction prices can still vary a lot even on the same day. Also, the periodic pattern of the daily average price suggests that there might be external market forces. In Section 4.4, we will discuss the possible explanations for the price variation.

²A lot is a bundle of homogenous products. The size of a lot can vary from a few units to more than a hundred units, and each unit consists of 20 to 80 stems, depending on the type and quality of flower.

³There might be log-in errors in the recorded transactions. For example, in some cases, winning prices were recorded as zero which clearly indicates an error.

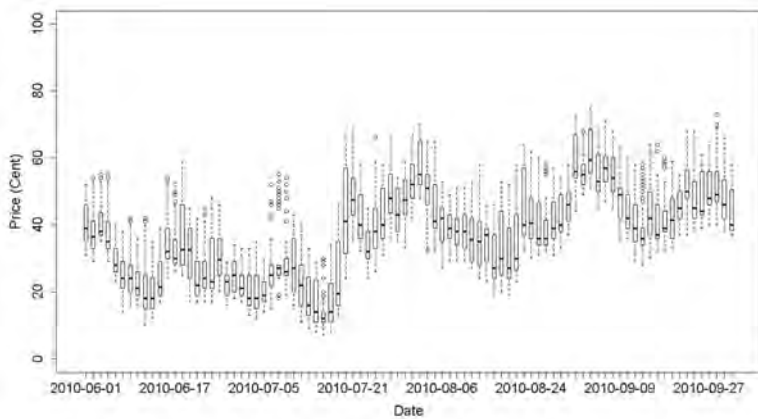


Figure 4.1: Price variation of roses during June 1 and September 30, 2010.

4.3.2 Cluster Analysis and Results

We use cluster analysis to explore the structural differences in bidders' bidding strategies. However, unlike previous studies (e.g., Bapna et al. 2004; Goes et al. 2012), in the DFA, we cannot observe when a bidder enters an auction, drops out from an auction, or the number of non-winning bids submitted to an auction, because at any moment of these auctions, only winning bids (winners' identities as well as their purchase quantities and winning prices) are revealed.

To deal with this challenge, we create four proxy variables to characterize bidders' behavior - Time of Entry in an Auction, Time of Entry and Time of Exit on a Day, and Frequency of Bid on a Day - using the rich transaction data which captures each bidder's winning bids across different auctions. Note that the introduction of the day-level variables is a novel contribution to the identification of bidding strategies in B2B markets. Given that bidders are participating in these auctions on a day-to-day basis, the day-level variables can help us to better relate the observed bidding behavior with the market conditions as well as the business profiles of different bidders. In the following, we will describe how we construct and operationalize each of these proxy variables.

Time of Entry in an Auction (TOE-A). During an auction, one of the key decisions for the bidders is to decide when to press the button. If it is too early, the bidder may end up paying a higher price than necessary, whereas reacting too slow may result in forgoing the opportunity to obtain the auctioned product. Since the DFA operate in a multi-unit sequential manner, each auction often consists of multiple rounds, although neither the bidders nor the auctioneers know *a priori* how many rounds it will take to finish the current auction. To account for the variability

of the length of an auction, we define a bidder's time of entry in a given auction as the ranking of the sub-auction where the bidder wins. For instance, if a bidder placed his bid in the second round and the entire lot takes ten rounds to finish, the TOE-A for this bidder in that specific auction is $2/10 = 0.2$. Since bidders often participate in many auctions on a given day, we take the average of a bidders's TOE-As across different auctions as his overall TOE-A on that day.

Time of Entry on a Day (TOE-D). Typically, there are multiple auctions for the same type of flowers on a day. Some bidders might act as observers in the first few auctions in order to learn about the market conditions, while others are bidding actively from the very beginning of an auction day. To capture such behavioral differences, we introduce the day-level proxy, TOE-D, which is defined as the ranking of the auction where a bidder places his first winning bid. Suppose there are 6 auctions for the specific flower on a given day, and a bidder's first winning bid happens in the 3rd auction, the TOE-D for this bidder is $3/6=0.5$.

Time of Exit on a Day (TOX-D). To couple bidder's entry decisions at day-level, we also need to look at the time when they drop out from the competition. Given the fact that most bidders in these auctions are buying on order, including bidder's time of exit together with their time of entry on a day can help us to identify more complex bidding patterns. Similar as TOE-D, we define TOX-D as the ranking of the auction where a bidder places his last winning bid.

Frequency of Bid on a Day (FOB-D). In our case, a bidders' frequency of bid at day-level refers to the number of winning bids he has placed on a given day. Different from the bidding frequency in English auctions which indicates bidders' involvement in an auction, in our case, FOB-D captures bidders' potential hedging behavior. That is, in order to avoid the potential loss of surplus gained from a sub-optimal bidding decision, some bidders tend to spread the purchase over multiple auctions even though they can fulfill their total demand in one auction.

We used the above classification variables in K-means clustering to identify the bidding strategies. A major challenge when applying this method is to determine the number of clusters. Given the exploratory nature of this research, we repeated K-means clustering with a range of values of K ($K_{\min} = 2, K_{\max} = 10$). According to the *Calinski-Harabasz* criterion (Milligan and Cooper, 1985), the optimal number of clusters is five. Note that good scores on an internal criterion (e.g., *Calinski-Harabasz* criterion) do not necessarily translate into the effectiveness of K-means clustering. An alternative is to look at the interpretability of the clustering results, which is often referred to as "external validity." In our case, we used ANOVA to test whether there are significant differences among the cluster centroids. The results from Table 4.2 show that all the four classification variables are significant.

Table 4.2: Cluster result ANOVA.

Cluster Attribute	Cluster Mean Square	Error Mean Square	F Mean Square	Sig.
TOE-A	88.855	0.022	3967.964	0.000***
TOE-D	97.418	0.021	4650.953	0.000***
TOX-D	100.998	0.022	4642.803	0.000***
FOB-D	30.955	0.014	2265.796	0.000***

Additionally, we conducted robustness test on the clustering results using cross validation. Specifically, we randomly split the observations into two parts. We applied K-means clustering ($K = 5$) to 2/3 of the observations (training data) and then using the identified cluster centers to label the rest 1/3 of the observations (test data). We then checked whether the labels of the test data are the same as the original ones obtained by running K-means clustering on the entire data. We repeated such process by 100 times and found that 99.27% of the observations from the test data have the same label as before. This shows that our clustering results are very stable.

We label the five clusters identified by K-means based on the characteristics conveyed by the corresponding centroid. Table 4.3 provides an overview of each cluster.

Table 4.3: Descriptives of the bidder clusters.

Clusters/Strategy	Bidders Adopting the Strategy		Mean (Std.) of Classification Variables			
	Cases	%	TOE-A	TOE-D	TOX-D	FOB-D
Conservative Strategies						
Early Evaluators (EE-C)	1578	23.70	0.30(0.14)	0.27(0.13)	0.28(0.14)	0.32(0.10)
Opportunists (O-C)	1455	21.80	0.79(0.14)	0.27(0.13)	0.28(0.14)	0.32(0.10)
Participators (P-C)	833	12.50	0.57(0.19)	0.28(0.16)	0.76(0.18)	0.73(0.19)
Forward-looking Strategies						
Early Evaluators (EE-F)	1388	20.80	0.31(0.14)	0.76(0.15)	0.77(0.15)	0.33(0.11)
Opportunists (O-F)	1411	21.20	0.81(0.14)	0.76(0.15)	0.78(0.15)	0.33(0.11)

To begin with, the first three clusters take a small mean value (approximately 0.3) in the dimension of TOE-D, and the rest two clusters take a large mean value (0.76 and 0.78, respectively) in the same dimension. A small value of TOE-D can be interpreted as a high bidding urgency, which might result from pre-committed orders, whereas a large value of TOE-D indicates considerable time and effort spent on monitoring and information collection prior to the first winning bids. In light of this, we label the strategies with small values of TOE-D as conservative and those with large values as forward-looking.

Further, the mean value of TOE-A across different clusters is also quite informative: *early evaluators* tend to place winning bids early in an auction, whereas *opportunists* tend to wait longer in an auction. Finally, the mean value of FOB-D for all clusters but *participators* is

approximately 0.3. Recall that the median of the number of auctions a bidder participates on a day is one (see Table 4.1). This suggests that *participants* on average won in more than two auctions on any given day. Overall, the five clusters identified by the K-means algorithm have a very straightforward interpretation in our sequential B2B auction context.

Given that all the bidders in this market are professional ones with sufficient bidding experience, the existence of these distinctive bidding strategies to a large extent challenges the popular conjecture that bidders' strategies will converge as they gain experience (Goes et al., 2012). In the following, we try to understand the observed heterogeneity by examining the antecedents and consequences of bidders' strategic choices.

4.4 Understanding Bidding Strategies

In this section, we first discuss the factors that affect bidders' choices of daily bidding strategies. We then analyze the outcomes associated with different bidding strategies and examine the potential interaction between the strategic factors and auction design parameters such as lot size and minimum purchase quantity.

4.4.1 Bidders' Choices of Bidding Strategies

Previous research has found a variety of economic, psychological and social factors that can affect bidders' decisions, although in many cases it is difficult to quantify these factors (Chakravarti et al., 2002). Given that bidders in the DFA are very familiar with the specific economic setting, we argue that they are less susceptible to psychological and social factors such as herding bias (Dholakia and Sotysinski, 2001) or addition to excitement (Herschlag and Zwick, 2000). Thus we focus on the economic factors. In particular, we examine three antecedents that are potentially critical to bidders' strategic decisions in the DFA: budget constraint, demand and transaction cost.

Budget Constraint

Budget constraints are an important feature of real-world B2B auctions. Previous research in the context of privatization of high-value public goods (e.g., standard treasury, spectrum or electricity auctions) has shown that in the presence of budget constraints, the conclusion of the revenue equivalence theorem no longer holds (Che and Gale, 2000; Laffont and Robert, 1996). When multiple objects are auctioned, Benoit and Krishna (2001) point out that it may be advantageous for a bidder to bid aggressively on one object to raise the price paid by his rivals and deplete their budgets so that the second object could be obtained at lower prices.

In the case of the DFA, bidders are also facing implicit or explicit budget constraints⁴. Following the above rationale, bidders with a high budget constraint (e.g., those small, family-run florists) would bid later on a day, in the hope that those who already fulfilled their demand or consumed their budget in earlier auctions drop out from the market. Additionally, unlike the classical setting of multi-unit auctions where only one unit is sold in each round, bidders' purchase quantity in the DFA have to meet the minimum required amount. Currently, auctioneers usually start with a low minimum purchase quantity at the beginning of an auction and gradually increase it as the auction proceeds. This means if a bidder with a high budget constraint misses the first few rounds of an auction, he might not be able to afford purchasing the products in that auction any more. Given these considerations, we hypothesize that

H1a: bidders with a high budget constraint are more likely to choose evaluator strategies over opportunistic strategies.

H1b: bidders with a high budget constraint are more likely to choose forward-looking, evaluator strategies than conservative, evaluator strategies.

Demand

Bidders in the DFA have, in general, multi-unit demand for any given type of flower. Such demand might be order-driven or speculation-based, i.e., some bidders are mainly purchasing on orders while others might decide to purchase more if they expect a "hot" market for certain flowers⁵. In the former case, bidders receive a commission fee which varies from 10 to 15 percent of the purchase price. Therefore, they are less likely to shade their bids or reduce the demand (Ausubel and Cramton, 2002; List and Lucking-Reiley, 2000), but bidding aggressively to make sure they acquire the products ordered by their customers.

On the other hand, if bidders have a large speculation-based demand, they might prefer to postpone their bidding in the first few rounds to learn the market conditions and trends (Jeitschko, 1998) or wait for a good bargain. Further, given that there are often multiple auctions with closely substitutable products, they may spread the demand over several auctions to maximize their expected payoff⁶. Therefore, we hypothesize that

H2a: bidders are more likely to choose opportunistic strategies over evaluator strategies when

⁴While the small buyers (e.g., small florists) are often facing hard constraint on borrowing or liquidity, it is less clear for those large buyers (e.g., international exporters). Sometimes, the choice of a budget itself is in itself a strategic decision. Nevertheless, drawing on the previous studies, we assume that budget constraints are endogenously determined prior to the start of an auction day.

⁵For example, most of the wholesalers tend to buy a lot more roses of high quality than their customers requested before Valentine's Day.

⁶This is also referred as modified demand reduction (Goes et al., 2010).

they have a large demand.

H2b: bidders are more likely to choose participator strategies over the evaluator strategies when they have a large demand.

Transaction Cost

Bidders' transaction costs refer to the time and effort invested by bidders in gathering information, preparing bids and participating in an auction. Carare and Rothkopf (2005) argue that bidders incur incremental transaction costs if they delay bidding in slow Dutch auctions. In the context of the DFA, although each transaction takes only a few seconds, monitoring the market dynamics is still very time-consuming, especially if the bidder has to be physically present in the auction hall. As we discussed before, the introduction of the online bidding channel, namely, KOA, has greatly reduce bidders' search cost and enhanced their monitoring capabilities. In other words, bidders who use the online channel incur less transaction cost as those bid via the traditional offline channel. This rationale leads to our next hypothesis:

H3a: bidders in the online channel are more likely to choose the opportunistic strategies over evaluator strategies.

H3b: bidders in the online channel are more likely to choose forward-looking, opportunistic strategies over conservative, opportunistic strategies.

Analysis and Results

We use multinomial logistic regression (MNL) to test the above hypotheses. The unit of analysis is bidder's strategy on a given day. MNL generalizes logistic regression to multi-classes (Greene, 2008). It is used to model the log odds of different outcomes (e.g., memberships) of a nominal dependent variable with a linear combination of independent variables. The main advantage of MNL is that it does not make any assumptions of normality, linearity, or homogeneity of variance for the independent variables. In our case, the generic model can be specified as follows:

$$\log\left(\frac{p(\text{strategy} = i)}{p(\text{reference strategy})}\right) = \log(\beta_0) + \beta_{1,i}\text{Budget} + \beta_{2,i}\text{Demand} + \beta_{3,i}\text{KOA}, \quad (4.1)$$

where Budget is a binary variable which takes value 1 if a bidder spent more than €100 purchasing the specific type of flower on a given day and 0 vice versa⁷, Demand is calculated

⁷Given that the exact information about bidders' budget is unknown, we calculate the average of a bidder's daily purchase cost and use that as the proxy of his daily budget. The distribution of a bidder's daily budget is

by dividing a bidder's total purchase quantity on a given day over the maximum of his daily purchase quantity during the four month period, and KOA indicates whether a bidder uses the online channel (KOA = 1) or not (KOA = 0).

We first set EE-C (conservative, early evaluator strategy) as the reference strategy in Equation 4.1. Table 4.4 and 4.5 provide the results from likelihood ratio tests. We can find that all the independent variables as well as their combination have a statistically significant effect on bidders' strategic choices.

Table 4.4: Model fitting results.

Criterion	Intercept Only	MNL Model
AIC	6594.6	5557.4
-2Log-Likelihood	6586.6	5525.4

Table 4.5: Analysis of effects.

Effect	Chi-Square	Degrees of Freedom	Sig.
Intercept	941.8	4	0.000***
Budget	626.7	4	0.000***
Demand	562.9	4	0.000***
KOA	49.3	4	0.000***

We ran the MNL model with different reference strategies and the parameter estimates are summarized in Table 4.6.

The numbers in Table 4.6 show the marginal change of log odds of choosing the specified strategy (the row strategy) over the reference strategy (the column strategy) change with respect to the specific independent variable. For example, we can see that the log odds of a bidder choosing the strategy O-C over strategy EE-C will increase by 1.14 when the bidder has a high budget. Similarly, the log odds of a bidder choosing the strategy O-F over strategy EE-F also increases by 0.99 when he has a high budget. This result supports our hypothesis H1a. However, it is unclear whether they would choose EE-F over EE-C, since the corresponding coefficients are insignificant. Thus H1b is not supported. Another observation is that for high-budget bidders, the log odds for choosing P-C over other strategies increase significantly.

Next, we can see that bidders with a large demand are more likely to choose participator strategies over opportunistic strategies, which in turn are more likely to be chosen over evaluator strategies. This result supports H2a and H2b. Further, Table 4.6 shows that online bidders are

right-skewed, with the minimum around €30 and the maximum more than €3000. We take the median, €100, as the threshold to determine whether a bidder has a large budget or low budget.

Table 4.6: Parameter estimates.

Strategy	Variable	Reference Strategy			
		Early Evaluators (EE-C)	Opportunists (O-C)	Participants (P-C)	Early Evaluators (EE-F)
Conservative	Opportunists (O-C)	Intercept	-0.160***		
		Budget	1.14***		
		Demand	1.34***		
		KOA	0.13		
	Participants (P-C)	Intercept	-4.42***	-2.82***	
		Budget	2.59***	1.45***	
		Demand	2.90***	1.56***	
		KOA	0.21*	0.08	
Forward-looking	Early Evaluators (EE-F)	Intercept	-0.24*	1.36***	4.18***
		Budget	0.15	-0.99***	-2.44***
		Demand	0.18	-1.16***	-2.72***
		KOA	-0.15	-0.28***	-0.36***
	Opportunists (O-F)	Intercept	-1.66***	-0.06	2.76***
		Budget	1.13***	0.00	-1.45***
		Demand	1.17***	-0.17	-1.73***
		KOA	0.38***	0.24***	0.17
					0.52***

more likely to choose opportunistic strategies over evaluator strategies, and forward-looking opportunistic strategies over conservative opportunistic strategies. Therefore, both H3a and H3b are supported.

Finally, given the current results in Table 4.6, we cannot tell whether an online bidder would choose the participator strategy or opportunistic strategy, with all other conditions being equal. Table 4.7 summarizes the findings of our hypothesis testing.

So far, we have shown that bidders' budget constraint, demand and channel usage (which is closely related to their transaction cost) have significant effect on their choices of bidding strategies. In the following, we will analyze the outcomes resulting from different strategies while taking into account various auction design parameters.

4.4.2 Outcome Analysis

Previous research in B2C context has shown that different bidding strategies might result in differences of winning likelihood and payoff (Bapna et al., 2004). In our case, given that all the observed bids are winning bids, it is not possible to compare the winning likelihood of different

Table 4.7: Summary of hypothesis test.

<i>H1a: bidders with a high budget constraint are more likely to choose evaluator strategies over opportunistic strategies.</i>	
<i>H1b: bidders with a high budget constraint are more likely to choose forward-looking, evaluator strategies than conservative, evaluator strategies.</i>	<i>H1a is supported. H1b is not supported.</i>
<i>H2a: bidders are more likely to choose opportunistic strategies over evaluator strategies when they have a large demand.</i>	
<i>H2b: bidders more likely to choose participant strategies over the evaluator strategies when they have a large demand.</i>	<i>H2a is supported. H2b is supported.</i>
<i>H3a: bidders in the online channel are more likely to choose the opportunistic strategies over evaluator strategies.</i>	
<i>H3b: bidders in the online channel are more likely to choose forward-looking, opportunistic strategies over conservative, opportunistic strategies.</i>	<i>H3a is supported. H3b is supported.</i>

strategies. As the result, we focus on the impact of bidders' strategic choices on their surplus. Since bidders' valuations of flowers are unknown, we measure their surplus extraction using loss-of-surplus which is defined as the difference between bidders' winning prices in an auction and the lowest winning price within the same auction.

Compared with single-unit auctions, bidders in sequential auctions have the opportunity to learn the market trend and opponents' information (e.g., demand, willingness-to-pay) from the previous rounds. Since opportunists tend to wait longer in an auction and place a bid later than the evaluators and participants (see Table 4.3), they are likely to acquire more market information and thus have a competitive advantage. Further, we expect that such competitive advantage is more prominent in auctions of larger lot size. Formally, we hypothesize that

H4a: Opportunistic strategies perform better than the other strategies in minimizing bidders' loss-of-surplus.

H4b: Opportunistic strategies perform better than the other strategies in minimizing bidders' loss-of-surplus in auctions with big lot size.

We use a hierarchical linear model (HLM) to test the above hypotheses. HLM was first proposed by education researchers (Raudenbush and Bryk, 2002) and it has become popular in many other research domains. The main advantage of HLM is that it allows for random variations in both the intercepts and slopes and thus it helps to control for the clustering of observations.

In order to control for the unobservable confounding effects which varies from day to day,

we normalize the winning prices on each day with respect to the minimum and maximum prices on that day, i.e., if the winning price in transaction j is P_j and the minimum and maximum prices on that day is P_{\min} and P_{\max} respectively, the normalized price is given by $(P_j - P_{\min}) / (P_{\max} - P_{\min})$. Thus the normalized price can be used directly as the measure of a bidder's loss-of-surplus in a given transaction. Further, since there is more than one supplier for the specific type of flower under consideration, we also include supplier dummies in the model to control for the potential reputation effects (Koppius et al., 2004). The full model specification is shown in Equation 4.2a-4.2d. In Equation 4.2a, the dependent variable \hat{P}_{jk} is the normalized winning price paid by bidder k in transaction j . *LotSize* refers to the total available units of the lot where transaction j belongs. *MinPQ* is the minimum purchase quantity in transaction j and *Supplier* is a set of dummy variables which are used to capture the potential reputation effects associated with the identities of suppliers. In Equation 4.2b-4.2d, $EE - C$, $O - C$, $P - C$ and $EE - F$ are dummy variables which correspond to the bidding strategies defined in Table 4.3. The baseline strategy is the forward-looking, opportunistic ($O - F$) strategy.

$$\hat{P}_{jk} = \beta_{0k} + \beta_{1k}LotSize_{jk} + \beta_{2k}MinPQ_{jk} + \gamma Supplier_j + \epsilon_{jk} \quad (4.2a)$$

$$\beta_{0k} = r_{00} + r_{01}EE - C_k + r_{02}O - C_k + r_{03}P - C_k + r_{04}EE - F_k + u_{0k} \quad (4.2b)$$

$$\beta_{1k} = r_{10} + r_{11}EE - C_k + r_{12}O - C_k + r_{13}P - C_k + r_{14}EE - F_k \quad (4.2c)$$

$$\beta_{2k} = r_{20} + r_{21}EE - C_k + r_{22}O - C_k + r_{23}P - C_k + r_{24}EE - F_k \quad (4.2d)$$

As the benchmark, we consider a simple linear model which does not account for clustering of observations, i.e.,

$$\hat{P}_{jk} = \beta_0 + \beta_1 LotSize_{jk} + \beta_2 MinPQ_{jk} + \gamma Supplier_j + \epsilon. \quad (4.3)$$

We applied Maximum-Likelihood (ML) method to estimate the coefficients in the above models. The results are summarized in Table 4.8 and 4.9.

The first thing to note from Table 4.8 is that the opportunistic strategies yield significantly lower winning prices⁸ than both participator strategies and evaluator strategies, which supports our hypothesis H4a. Also, we can see that both *LotSize* and *MinPQ* have a negative effect on price, although the magnitude of such effect is rather small.

⁸Since the dependent variables in Equation 4.2a and 4.3 are normalized with respect to the daily maximum and minimum of winning prices, the coefficients in Table 4.8 and 4.9 cannot be interpreted as marginal changes of winning prices with respect to the specific independent variable. To see the marginal effects of these variables, the coefficients need to be multiplied by the corresponding price gap ($P_{\max} - P_{\min}$) on a given day, e.g., if the price gap is 30 cent, the conservative, early evaluators would, on average, pay 2 cent more than the forward-looking opportunists.

Table 4.8: Estimation results of the HLM model.

Variable	Coefficient	Std. error	Sig.
Intercept	0.3968	0.0125	0.0000***
EE-C	0.0743	0.0181	0.0000***
O-C	-0.0417	0.0186	0.0248*
P-C	0.0586	0.0159	0.0002***
EE-F	0.1038	0.0186	0.0000***
LotSize	-0.0005	0.0000	0.0000***
MinPQ	-0.0059	0.0031	0.0536 .
S5547	0.3788	0.0056	0.0000***
S79520	-0.4431	0.0066	0.0000***
S80547	0.4037	0.0078	0.0000***
S562450	-0.1791	0.0065	0.0000***
EE-C : LotSize	0.0005	0.0001	0.0000***
O-C : LotSize	0.0003	0.0001	0.0187*
P-C : LotSize	0.0001	0.0001	0.2774
EE-F : LotSize	0.0000	0.0001	0.9998
EE-C : MinPQ	-0.0155	0.0055	0.0051**
O-C : MinPQ	0.0115	0.0048	0.0161*
P-C : MinPQ	-0.0088	0.0041	0.0330*
EE-F : MinPQ	-0.0216	0.0060	0.0003***

Table 4.9: Estimation results of the simple linear model.

Variable	Coefficient	Std. error	Sig.
Intercept	0.4507	0.0061	0.0000***
LotSize	-0.0003	0.0000	0.0000***
MinPQ	-0.0160	0.0014	0.0000***
S5547	0.3770	0.0057	0.0000***
S79520	-0.4417	0.0068	0.0000***
S80547	0.4068	0.0080	0.0000***
S562450	-0.1843	0.0066	0.0000***

Further, we find significant interaction effects between bidding strategies and the two auction design parameters. Specifically, the results suggest that the prices paid by forward-looking opportunists ($O - F$, the baseline used in the HLM model) decrease at a faster rate than conservative bidders ($EE - C$, $O - C$) when *LotSize* increases. Thus H4b is supported. On the other hand, the evaluators and participators are more sensitive to the increase in *MinPQ* – the prices paid by these bidders decrease faster than opportunists when *MinPQ* increases.

Finally, both Table 4.8 and 4.9 suggest there are significant reputation effects, for example, the normalized prices of products from Supplier 5547 and Supplier 80547 are higher than products from others. At the first sight, the existence of such reputation effects might raise concerns about the cluster analysis, because if bidders do have preferences over the suppliers, this might influence their entering decisions in an auction. However, since the order of lots from different

suppliers is determined by a random draw every day, it is highly unlikely that some suppliers' products would always be auctioned earlier than others.

We also compared the performance of the two models. The AIC and BIC values for the hierarchical model are smaller (-5745, -5604) than the simple linear model (-5476, -5420), indicating that the incorporation of the clustering results significantly improves the model fit.

4.5 Discussion

We developed a robust taxonomy of bidding strategies in a multi-channel B2B market. Although there are similarities in the empirical characterization of bidding strategies across the B2B and B2C contexts, some of the regularities observed in the B2C context do not carry to the B2B context. For example, we do not observe any sip-and-dippers (Bapna et al., 2004). This to some extent could be attributed to the differences in the auction mechanism - in the English auction, we can observe all the placed bids (both winning and losing bids) whereas in the Dutch auction, only winning bids get revealed. However, given the sequential nature of these auctions, it is still surprising that bidders did not exhibit modified demand reduction (Goes et al., 2010) at auction level, i.e., purchasing a small amount in early rounds and a large amount in later round. Further, we did not identify any recurrent or intermittent strategies as described by Goes et al. (2012) in their study of sequential B2C markets. In fact, the majority of the bidders, except for the participators, seem to be actively bidding only for a short time (either early or late) on a given day (see Table 4.3 for the time of entry and exit on a day).

We examine the antecedents of the observed heterogeneity in bidding strategies. Our findings show that bidders' strategic choices can be explained by their budget constraint, demand as well as their channel affiliation. Overall, bidders with a high budget and a large demand are likely to choose participator or opportunistic strategies rather than evaluator strategies, and bidders who use the online bidding channel are more likely to adopt the opportunistic strategies. At the outset, these results are consistent with the previous empirical auction literature. However, the findings from our analysis offer a higher level of granularity. To the best of our knowledge, this is the first empirical study that examines bidders' strategic behavior in multi-channel B2B auctions.

Further, we analyzed the economic impact of different strategies. Our results suggest that opportunists outperform both participators and evaluators in maximizing their surplus. This differs from the previous study by Bapna et al. (2004) where the authors show the participators perform best among non-agent bidders in terms of surplus extraction. Such difference can be attributed to the nature of auctions and bidders' business constraint. Specifically, Bapna et al. (2004) examine the Yankee auctions where the market clears only once at the end of a

pre-specified time period. Therefore, the participators can always revise their bids by closely monitoring the market dynamics during an auction. In the case of the DFA, bidders do not know when the market clears at auction level. Also, we have seen that participators are likely to have a large demand than the other types of bidders and in many cases, fulfilling the orders from their customers *per se* is more important than getting the products at the lowest possible price.

We also find a significant main effect of lot size, which is consistent with Mithas and Jones (2007) but different from earlier work in B2C auctions by Bapna et al. (2001). In particular, we have seen that lot size has a negative overall effect on the winning price of a given product, although such overall effect is moderated by bidding strategies.

4.5.1 Implications

The findings and results from the current study have important implications for theory and practice. From the theoretical perspective, the identification of the five distinctive strategic types in the DFA challenges the conventional notion that bidders' strategies converge as they gather more and more experience by participating in the competition repeatedly and calls for a dynamic instead of static view in studying bidding behavior in complex environment. Additionally, previous research by Goes et al. (2012) show that in B2C sequential auctions bidders are more likely to choose intermittent strategies as they gain experience by participating in many auctions, however, in our case, we did not find any bidder following these strategies despite that they are all experienced in these auctions. Such discrepancy between the strategies pursued in B2C and B2B context underscores the necessity to understand the differences in bidders' incentive structures in the two types of bidding environments. In this sense, our explanatory model which maps bidders' choices of strategies to their business constraints and requirements provide a useful starting point.

Further, our findings shed new light on the declining price anomaly of sequential auctions⁹. Currently, the explanations to declining price in sequential rounds can be cast into two broad categories. The first category consists of studies that examine bidder heterogeneity in terms of risk profiles (McAfee and Vincent, 1993) or product heterogeneity (Engelbrecht-Wiggans, 1994) whereas the second category focuses on the informational effect in the sequential auctions (Jeitschko, 1998). Our analysis of the antecedents and consequences of bidding strategies

⁹Within the symmetric independent private value paradigm, Weber (1983) has shown that in sequential auctions where bidders have single-unit demand, the equilibrium price path under the standard auction formats and pricing rules follows a martingale – the expected winning price in the future round and the current round are the same. However, such neat theoretical results are not supported by empirical findings. For example, McAfee and Vincent (1993) have found price declines in sequential wine auctions. Similar declining price phenomena are also observed in art auctions (Beggs and Graddy, 1997) and flower auctions (Van den Berg et al., 2001). The contradiction between theory and empirical findings has been coined as declining price anomaly.

suggest that both bidder heterogeneity and the informational effect play a role in determining the price path in sequential auctions. More specifically, the early evaluators are likely to be more risk averse and they would rather pay a risk premium at the beginning of an auction to ensure the fulfillment of orders. On the contrary, the opportunists exhibit a certain degree of gambling behavior: in order to acquire the products at the best price, they are willing to trade the opportunity to purchase in earlier rounds for more information about the market conditions.

From the managerial perspective, our results provide useful insights to auctioneers in their complex decision-making in the DFA. The auctioneers in the DFA represent the growers. As such, their main objective is to realize high prices. Besides, it is also important that they achieve a quick turnaround since flowers are perishable goods. By controlling key auction parameters such as starting prices, minimum purchase quantities and reserve prices, the auctioneers can influence the dynamics of the auction. The taxonomy can be viewed as a micro-segmentation of the market and thus is useful in optimizing the auction process. For example, currently, the lot sizes are determined by the suppliers who have little information about the strategic characteristics of the buyers. Auctioneers on the other hand can observe the bidders' behavior in real time. Given the significant interaction effect between lot size and bidders' strategies, auctioneers should tailor the decisions on lot sizes to the composition of bidder population. In addition, we have found that evaluators and participators are more sensitive than opportunists to the change of minimum purchase quantity. Therefore, auctioneers might need to think of alternative strategies other than increasing the minimum purchase quantity in order to speed up the market process. In light of the declining price trend and the competitive advantage of opportunists, auctioneers should also develop better information transparency strategies across different market channels. Finally, the separation of conservative strategies and forward-looking strategies along the day-level entering time, i.e., TOE-D suggests that there is great potential to customize the auction schedules and further improve the total revenue.

4.5.2 Limitations and Future Work

Our paper bears several limitations that, nevertheless, open up avenues for future research. For example, we do not take into account for the potential screening effects when performing the cluster analysis. According to the results from the outcome analysis, if bidders' entering decisions are conditional on their preferences over the suppliers, we might need to adapt the current explanatory model for bidders' strategic choices accordingly and the implications might be different. Further, we chose to analyze bidders' strategies at day-level instead of auction-level because it helps us to better capture the B2B features of these auctions. However, this makes it difficult to analyze bidders' strategic changes across different auctions over a day. Nevertheless, given the nature of these auctions, i.e., high variation of auction length and only winning bids

are visible, we think that the results from sequence analysis of winning bids across different auctions might be less useful than in the English type of online auctions.

Another potential weakness with the current study is that we have focused on the auctions of a specific type of product when examining bidders' behavior. In reality, bidders might have to deal with constraints of product complementarity in their bidding decisions. However, we do not have access to any data set that consists of transactions across different product groups. We plan to investigate these issues by computational simulations.

Currently, we are building a rich simulation platform, taking into account the strategic patterns of the bidder population. Such platform allows us to experiment with alternative auction designs and different information revelation policies. The results from these experiments will provide useful implications to practitioners in B2B markets.

Chapter 5

Information Transparency in Sequential B2B Auctions

5.1 Introduction

The proliferation of electronic marketplaces has brought tremendous changes to the business world. Compared with the traditional brick-and-mortar markets, these Internet-enabled marketplaces substantially reduce consumer' search costs (Bakos, 1997) and thus enable them to better discern products that best fit their needs. Firms, however, are forced to deal with the paradox of the benefits brought by the electronic marketplaces (Granados et al., 2010). On one hand, the increased availability of information allows them to strategically target consumers in various markets. On the other hand, the increased transparency of markets makes it more difficult to capture profits because their competitors and consumers are better informed (Porter, 2001). The two sides of the coin of information transparency for firms motivate us to study the strategic revelation of information in Business-to-Business (B2B) environment.

Information transparency, which is defined as the level of availability and accessibility of market information to its participants (Zhu, 2004), is deemed to be good to the whole supply chain because it helps improve the allocative efficiency (Cachon and Fisher, 2000; Lee et al., 2000; Patnayakuni et al., 2006). Yet it affects the two sides of the market, i.e., buyers and sellers, very differently. For example, using a comprehensive analytical model, Zhou and Zhu (2010) show that depending on the competition mode of the downstream industry, one side will always be worse off under the increased transparency enabled by the electronic B2B markets, although the total welfare of market participants are increased regardless of the competition mode.

Given the conflict of interest in the market, a natural question for the B2B market-maker is how to design and implement the information revelation policies for its own benefits¹. What

¹According to Yoo et al. (2007), B2B markets can be classified into three types based on their ownership structure: buyer-owned marketplaces, seller-owned marketplaces, and neutral marketplaces that are owned by in-

information should be disclosed? Under what conditions? The answers to these questions depend largely on the real-world context.

In this paper, we focus on information transparency in a complex B2B setting, the Dutch Flower Auctions. The Dutch Flower Auctions are multi-unit, sequential, Dutch auctions. They account for more than 60% of the global flower trade and generate over 4 billion euros annually. The sheer magnitude of transactions in this market makes it important to carefully weigh the trade-offs of different transparency strategies. Using a field experiment, we seek to understand how the disclosure of winners' identities influence the behavior of market participants and the final outcome in these auctions.

Drawing upon the linkage principle (Milgrom and Weber, 1982b), which basically states that a seller can expect to increase revenues by providing more information to bidders, both before and during the auction², we expect that disclosing winners' identities would yield higher revenue for the sellers in these auctions. Surprisingly, however, our analysis of the experimental data shows that bidders, on average, pay significantly lower (4.5%) prices when auctioneers disclose the winners' identities rather than withholding such information. Further, in light of the literature on declining price anomaly (Van den Berg et al., 2001), we also look into the informational effects of winners' identities on price dynamics at auction-level, and find that withholding winners' identities tends to mitigate the declining trend in a sequential auction.

Since bidders in these auctions participate in the bidding activities repeatedly over a long period³, it is likely that the failure of the linkage principle is due to bidders' tacit collusion (Bajari and Yeo, 2009; Sherstyuk and Dulatre, 2008). In general, collusion is easier to sustain in environments that are more transparent. Therefore, we examine the relationship between bidders' participatory patterns and revelation policies (i.e., whether winners' identities are disclosed or not). Our analysis shows that bidders who restrict their purchases to a few number of sellers (thus more likely to collude), on average, pay lower (9.8%, statistically significant) prices when winner's identities are disclosed. However, when such information is not available, such price-related advantage is mitigated substantially.

Our paper makes several contributions to the growing body of information systems (IS) literature on the design of transparency strategies in B2B markets. First of all, we present em-

dependent third parties. The ownership structure has a direct impact on the market-maker's choice of transparency strategies.

²The linkage principle was derived under symmetric affiliation (Milgrom and Weber, 1982b). In our case, while bidders in the flower auctions typically serve distinct market segments and there are certainly individual-specific, private-value components in their purchases, common-value components surely exist, too. For example, Koppius et al. (2004) have shown that sellers' reputation plays a critical role in determining the final transaction prices, suggesting that there is some unknown quality that matters to all potential buyers.

³According to the auctioneers, most of the bidders have been participating in the bidding for five or sometimes ten years.

pirical evidence that linkage principle might not hold for B2B sequential Dutch auctions. In other words, sellers might be worse off by revealing more information to bidders. Compared with previous studies, for example, Arora et al. (2007); Greenwald et al. (2010); Zhu (2004)), we study information revelation policies in a complex real-world environment. Additionally, most of the existing studies focus on the revelation of bids in English auctions, we on the other hand examines the revelation of winners' identities in Dutch auctions where only winning bids are revealed and thereby, less transparent by their nature. To the best of our knowledge, no prior work has compared different revelation policies in Dutch auctions using field data. Secondly, our results provide additional insights of the declining price anomaly (Ashenfelter, 1989; McAfee and Vincent, 1993; Van den Berg et al., 2001). From the managerial perspective, our findings offer a cheap yet effective way to mitigate the declining trend of prices by concealing winners' identities in the multi-unit, sequential Dutch auctions.

The rest of this chapter is organized as follows. Section 2 provides a review of related literature. Section 3 introduces the empirical setting. In Section 4, we first present the econometric model and the empirical results, and continue with a discussion of robustness checks and additional analysis. Finally, Section 5 summarizes the findings and discusses the implications .

5.2 Related Literature

In this section, we discuss two streams of literature on sequential auctions that are closely related to the current study.

5.2.1 Information Revelation in Auctions

The popularity of online auction platforms has drawn an increasing research interest in the design of information-revelation policies (Arora et al., 2007; Greenwald et al., 2010). While Milgrom and Weber (1982a)'s linkage principle suggests that sellers typically benefit by providing more information to bidders⁴, in many real-world applications, the information-revelation problem is more subtle, for example, sellers might not be able to directly release the information, or they might not have full control of bidders' perceived content of the information (Abraham et al., 2013).

When it comes to multi-unit (sequential) auctions, the analysis of different information-revelation policies becomes more difficult and the findings concerning the linkage principle are mixed. Perry and Reny (1999) provide a counter-example where the linkage principle breaks

⁴One can imagine numerous circumstances where the disclosure of information can have negative impact on the auction outcome (for example, if the seller revealed information about the defects of the item under auction), however, the remarkable implication from the linkage principle is that, *ex ante*., releasing more information can help increase the seller's expected revenue.

down in multi-unit auctions. On the contrary, Arora et al. (2007) and Greenwald et al. (2010) show that complete information policy (which minimizes the uncertainty on market structure and opponents' cost structure, respectively) generates higher buyer surplus in sequential procurement auctions, suggesting that linkage principle holds for these auctions.

So far, most of the existing research on information-revelation policies in auctions is purely analytical, i.e. the results are derived from equilibrium analysis of different auction models where bidders are assumed to be strictly rational. The few papers that empirically tests the linkage principle using controlled lab experiments (Kagel and Levin, 1986; Levin and Smith, 1996), the results are again inconclusive. Specifically, researchers find that in experiments involving inexperienced bidders, the winner's curse⁵ due to overbidding is more prevalent in sealed-bid auctions (less transparent) than English auctions. This leads to higher revenues in sealed-bid auctions than English ones, contrary to the prediction of linkage principle. However, in experiments involving experienced bidders, the winner's curse is alleviated and sellers' revenues are higher in English auctions, which is consistent with the linkage principle.

In the current study, we examine the impact of information revelation policy on seller revenue using a large field experiment. Compared with previous work, our empirical setting features a complex, dynamic market where bidders are highly experienced.

5.2.2 Declining Price Anomaly

Within the symmetric independent private value paradigm (IPVP), Weber (1983) shows that in sequential auctions where bidders have single-unit demand, the equilibrium price path under the standard auction formats and pricing rules follows a *martingale*⁶ – the expected winning price in the future round and the current round are the same. When bidders have multi-unit demand, Donald et al. (2006) demonstrate that the equilibrium price path follows a super-martingale, i.e., the equilibrium price rises as a sequential auction proceeds. However, such neat theoretical results are not supported by empirical findings. Ashenfelter (1989) and McAfee and Vincent (1993) have found price declines in sequential wine auctions. Similar declining price phenomena are also observed in art auctions (Beggs and Graddy, 1997) and flower auctions (Van den Berg et al., 2001).

The contradiction between theory and empirical findings, which has been coined as *declining price anomaly*, has attracted a significant amount of research which attempts to offer plausible explanations. These explanations can be cast into two broad categories. The first category consists of studies that examine bidder heterogeneity (McAfee and Vincent, 1993) or product

⁵For more details about winner's curse, see P. 84 in (Krishna, 2002).

⁶In probability theory, a martingale is a model of a fair game where knowledge of past events never helps predict the mean of the future winnings (Williams, 1991).

heterogeneity (Engelbrecht-Wiggans, 1994). The second category focuses on the informational effect in the sequential auctions. For example, Jeitschko (1998) associates the declining price anomaly with two unique learning effects in sequential auctions—a direct effect where information from the previous rounds is used to form the current bids and an anticipation effect where bidders try to account for the effect of their earlier bids on their opponents’ bids.

In this study, we do not attempt to probe into the causal relationships between various endogenous or exogenous factors and the price decline. Instead, we are interested in whether information revelation policy affects the declining trend in fast-paced sequential auctions.

5.3 Empirical Setting

In this section, we provide details of the experiment design and the data collected from the field experiment.

5.3.1 Experimental Design

We conduct a quasi-natural field experiment (Harrison and List, 2004) to investigate how the disclosure of winners’ information affect the bidding dynamics and outcomes in the complex environment of the Dutch Flower Auctions. The experiment ran from November 19 to December 7, 2012 on a clock which auctioned chrysanthemums⁷ at a major site. Aside from the transaction data from the *treatment* site during the experimental period, we also collected data from the same site before the experimental period (from October 29 to November 16), and data from a *control* site⁸ before and during the experimental period.

The experimental treatment was implemented as follows. After the first bidder stopped the clock and made a purchase, all the bidders could see the winning price (indicated by a marker on the clock) and the remaining unit(s), just as in the regular setting of the Dutch Flower Auctions. However, the winner’s identity was removed from the clock screen. In other words, none of the bidders, except the winner herself, knew who was the winner in the current round⁹.

Figure 5.1 provides an overview of the experimental design. Basically, bidders could always observe winners’ identities at both the treatment site and control site prior to the experiment

⁷Chrysanthemum has the second largest transaction amount among all the auctioned products. In 2012, more than 1.1 million units of chrysanthemums were traded.

⁸Technically speaking, with the introduction of online channel, bidders can choose to purchase from any one of the six auction sites within the country. However, bidders usually choose the one closest to their distribution center in order to minimize the logistic cost. This is particular the case for large buyers (e.g., wholesalers). However, other than the operational and logistic cost, there is no *a priori* structural differences in terms of product, auction mechanism and policy between different auction sites.

⁹As the researcher, we always have access to the winners’ identities since they were registered in the auctioning system during each transaction.

period, whereas during the experiment period only bidders at the control site had access to such information. To make sure that bidders were well informed about the change during the experiment period, at the end of October 2012, the auction department of the company held a Webinar where auctioneers and bidders could exchange their thoughts. As a follow-up survey, we also held interview sessions with several buyers who had participated in the bidding during the experimental period.

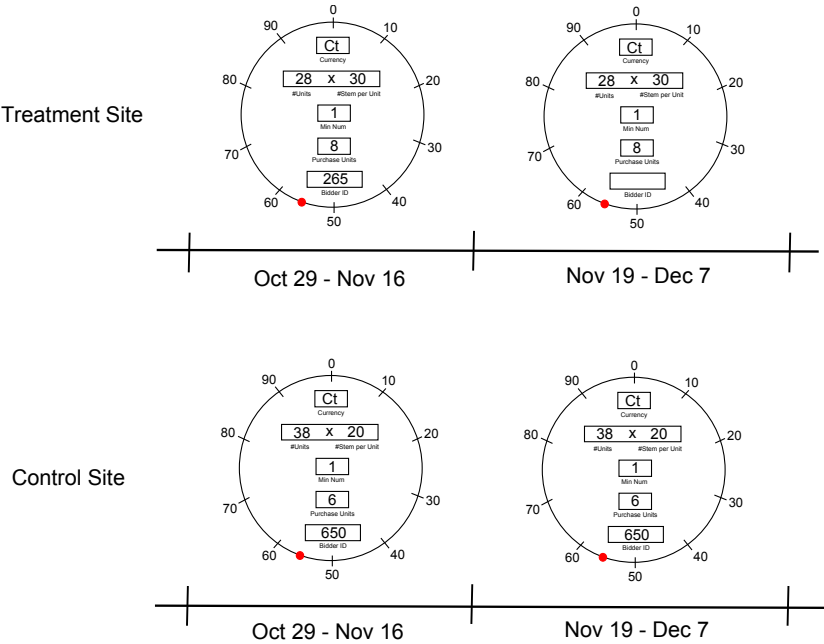


Figure 5.1: Overview of the experimental design.

As opposed to those controlled lab experiments examining information revelation policies (for example, Cason et al. (2011)), the main advantage of our field experiment is that it retains the rich interaction (both explicit and implicit) and dynamics from the real-world B2B auctions and thus allows us to better investigate the nuances of professional bidders' behavior that *naturally* occurs under different revelation policies.

5.3.2 Data and Preliminary Analysis

In order to control for the product heterogeneity, we selected the transactions of *Chrysanthemum spray white/yellow GP*. The total number of transactions at the treatment site during period I (pre-experiment) is 11,613 (from 1,798 auctions) where 10,427 transactions were made via the online channel (See Section 2.2.1), and the total number of transactions during period II

(experiment) is 11,899 (from 1,855 auctions) where 10,833 transactions were through the online channel.

Table 5.1 summarizes the descriptive statistics. We can see that while buyers' bidding behavior ¹⁰ does not vary much from period I to period II, the average winning price increases considerably (14.6%). In addition, we split the transactions into two sub-samples: transactions made via the online channel and those via the traditional offline channel (onsite bidding), and calculated the average winning prices during the two periods. Figure 5.2 shows that the average winning prices are higher during the experiment period for both channels (14.8% for the online channel and 15.4% for offline channel).

Table 5.1: Descriptive statistics of the dataset.

Statistics	Lot Size		# of bidders per auction		Bid frequency (auction)		Bid frequency (day)		Price (cent)		Purchase amount	
	I	II	I	II	I	II	I	II	I	II	I	II
Mean	68.0	64.2	6.3	6.2	1.0	1.0	4.3	4.5	26.7	30.6	10.5	9.9
Median	57.0	52.0	6.0	6.0	1.0	1.0	3.0	3.0	25.0	30.0	5.0	5.0
Std.	59.9	53.3	4.1	4.0	0.2	0.2	4.3	4.6	9.6	7.3	16.8	14.9
Skewness	2.4	2.3	1.1	1.0	6.2	6.3	2.1	2.2	0.4	0.1	6.1	5.6
Minimum	5	4	1	1	1	1	1	1	5	5	1	1
Maximum	580	450	32	32	3	4	29	34	62	66	347	264

In light of the literature on declining price trend in sequential auctions, we also examined the evolution of transaction prices at auction-level during the pre-experiment and experiment periods, respectively. Given the potential unobserved heterogeneity across lots, we normalized the transaction prices in subsequent rounds with the first round in an given auction. The comparison is depicted in Figure 5.3, where we have two observations. First, the price exhibits an overall declining trend in both the pre-experiment and experiment periods. Second, the declining trend seems to be alleviated during the experiment period. More specifically, the mean values of normalized prices in the subsequent rounds during the experiment period are higher than those observed during the pre-experiment period, and the variances of the normalized prices also shrink considerably during the experiment period.

These aggregate-level results seem to suggest that withholding winners' identities has a positive impact on the transaction prices. However, the main concern about such model-free evidence is that it does not control for any potential systematic changes in market conditions. For example, it is likely that there was a higher demand during the experiment period, or bidders

¹⁰We use number of rounds a bidder participated in an auction, i.e., Bid frequency (auction) and the number of auction a bidder participated on a given day, i.e., Bid frequency (day) to characterize bidders' bidding behavior in the two periods.

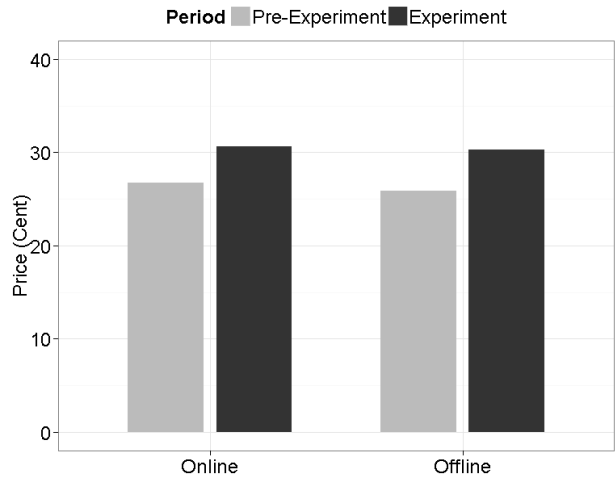


Figure 5.2: Comparison of average winning prices in pre-experiment and experiment period.

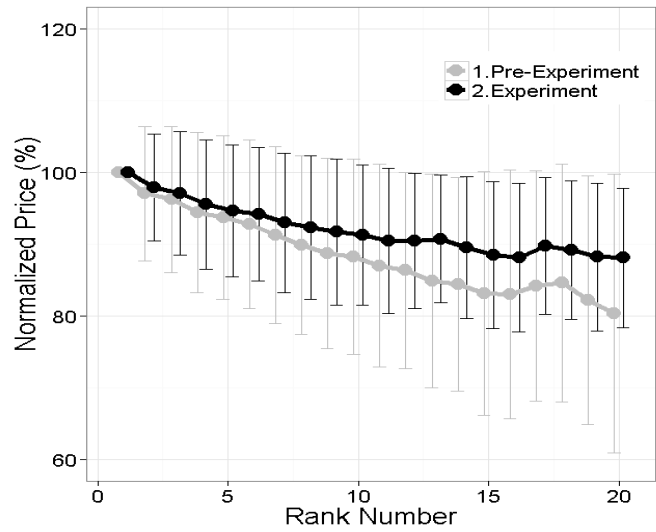


Figure 5.3: Comparison of price dynamics at auction-level during pre-experiment and experiment periods. The rank number denotes the rank of the current transaction, i.e., if a transaction was made in the 2nd round, the rank number is 2. The vertical bars denote one standard deviations of the normalized prices in each round.

who participated in the auctions during the experiment period are not the same ones participating in the pre-experiment period.

5.4 Econometric Model

In order to identify the causal impact of the policy change regarding information transparency on transaction prices of sequential auctions, we use the so-called difference-in-differences (DID) technique by taking the matched sample from the control site.

DID is a quasi-experiment technique that models the treatment effect by estimating the difference between outcome measures at two time periods for both the treated subjects and the controls and then comparing the difference between the treated and control groups (Meyer, 1995).

If we use $t = 0$ to denote the pre-experiment period and $t = 1$ to denote the experiment period, $\log P_{i,t}$ to denote the log-transformed price for transaction i in period t , the underlying model for DID can be written as follows:

$$\log P_{i,t} = \beta_0 + \beta_1 T_t + \beta_2 G_i + \beta_3 G_i * T_t + \gamma X_{i,t} + \epsilon_{i,t}, \quad (5.1)$$

where G_i and T_t are both dummy variables, G_i taking the value 1 if transaction i is from the treatment site and 0 if it is from the control site, and $T_t = 1$ if $t = 1$ and 0 otherwise. $X_{i,t}$ is the control variable for the observed covariates such as product characteristics (e.g., stem length, blooming stage) and auction design parameters (e.g., minimum purchase quantity). The DID estimator is just the OLS estimate of β_3 , i.e., the coefficient of the interaction term. Note that β_1 summarizes the way that both the treatment and control groups are influenced by time. Additionally, all the time-invariant differences between the two groups are captured by β_2 . Therefore, the model specified in Equation 5.1 ensures that any variables that remain constant over time (which may not be observed) that are correlated with the outcome variable will not bias the estimated effect.

5.5 Results

In this section, we first presents the main results and then continue with the discussion of robustness check and additional analyses.

5.5.1 Main Results

We applied the DID model to the pooled panel data, i.e., the transactions from the treatment site and control site during the pre-experiment and experiment period¹¹. In total, we have 54592 transactions. Table 5.2 shows the result of the regression. For the demonstration purpose, we only included the coefficients related to the treatment.

Table 5.2: Estimation results of the DID model (entire sample).

Coefficient	Estimate	Std. error	P-value
Treatment period (β_1)	0.127	0.003	0.000 ***
Treatment site (β_2)	-0.005	0.012	0.674
Treatment period * Treatment site (β_3)	0.045	0.005	0.000 ***
Adjusted R^2 : 0.187			

We can see that the winning price increased by 4.5% at the treatment site during the experiment period. In other words, withholding winners' identities led to significantly higher revenue. Given that the sheer magnitude of these auctions, the impact of the change in information revelation policy can be remarkable.

Given that most bidders participated in these auctions via the online channel (see data description in Section 5.3.2), we would like to know whether the effect of policy change holds for both online and offline bidders. In order to assess how the withholding of winners' identities influence bidders in different channels, we re-estimated Equation 5.1 for transactions made via the online and offline channel, respectively. Table 5.3 and 5.4 show that both online and offline bidders paid more under the treatment condition: on average, online bidders paid 4.1% higher and offline bidders paid 6.5% higher when winners' identities were concealed. This suggests that the loss of the winners' information could not be compensated by the other market state information (Koppus, 2002) communicated in the auction room.

Further, since the preliminary analysis suggests that concealing winners' identities has some mitigation effect on price declining trend, we also examined the impact of the policy change on price dynamics at lot-level, using a hierarchical linear model (HLM). HLM was first proposed by education researchers (Raudenbush and Bryk, 2002) and it has become popular in many other research domains. The main advantage of HLM is that it allows for random variations in both the intercepts and slopes and thus it helps to control for the clustering of observations. The

¹¹Before fitting the field data to the DID model, we also checked bidders' potential switching behavior, i.e., bidders who participated in the auctions at the treatment site during the pre-experiment period did not switch to auctions at the control site during the experiment period, or the other way around. After going through all the transaction details of the specific flowers during the 6 weeks, we did not find evidence of switching.

Table 5.3: Estimation results of the DID model on the sub-sample of online transactions.

Coefficient	Online transactions		
	Estimate	Std. error	P-value
Treatment period (β_1)	0.128	0.004	0.000 ***
Treatment site (β_2)	0.005	0.014	0.677
Treatment period * Treatment site (β_3)	0.041	0.006	0.000 ***
Adjusted R^2 : 0.185			

Table 5.4: Estimation results of the DID model on the sub-sample of offline transactions.

Coefficient	Offline transactions		
	Estimate	Std. error	P-value
Treatment period (β_1)	0.125	0.007	0.000 ***
Treatment site (β_2)	-0.133	0.035	0.000 ***
Treatment period * Treatment site (β_3)	0.065	0.015	0.000 ***
Adjusted R^2 : 0.204			

full model is specified as follows:

$$\text{Level 1 : } \log \frac{P_{t,k,l}}{P_{t,k-1,l}} = \gamma_{0,t} + \gamma_{1,t}(k-2) + \gamma_{2,t}(\text{Available} - 2) + \epsilon_{k,l}, \quad (5.2a)$$

$$k > 1, \text{Available} > 1,$$

$$\text{Level 2 : } \gamma_{0,t} = w_{00} + w_{01}T_t + u_{0,t}, \quad (5.2b)$$

$$\gamma_{1,t} = w_{10} + w_{11}T_t, \quad (5.2c)$$

$$\gamma_{2,t} = w_{20} + w_{21}T_t, \quad (5.2d)$$

where l refers to the lot index, k is the rank number of the transaction, and *Available* stands for the available units in the current round. Since we are comparing the transaction prices in consecutive rounds within an auction, we only need transaction data from the treatment site to estimate the model in Equation 5.5.1- 5.2d. This is different from previous analyses. Further, in Equation , instead of a simple linear regression on the rank number of the transaction, we follow the practice proposed in Van den Berg et al. (2001) where the difference of the logarithmic prices in consecutive rounds is used as the dependent variable. The benefits of such practice are two-fold: (i) it controls for potential confounding factors that influence the length (the maximum of the rank number) of an auction and the transaction prices simultaneously, (ii) it addresses the potential correlation of prices within a sequential auction, which may result in biased estimation.

It follows from Table 5.5 that concealing winners' identities has significant mitigation effect

on the price declining trend, however, the magnitude of such effect is negligible when compared to the average price decline.

Table 5.5: Impact of policy change on lot-level declining price trend.

Coefficient	Estimate	Std. error	P-value
Intercept (w_{00})	-0.0215	0.0012	0.000 ***
Treatment period (w_{01})	0.0028	0.0016	0.0894 .
Rank number (w_{10})	0.0015	0.0002	0.000 ***
Available units (w_{20})	- 0.00005	0.00001	0.000 ***
Treatment period * Rank number (w_{11})	-0.0002	0.0002	0.2815
Treatment period * Available units (w_{21})	0.00005	0.00002	0.003 **

5.5.2 Robustness Check

Because bidders were informed about the policy change prior to the experiment period, it is likely that the observed differences in transaction prices were due to the novelty effect or *Hawthorne* effect, which is defined as the problem in field experiments that subjects' knowledge that they are in an experiment modifies their behavior from what it would have been without that knowledge (Adair, 1984). Therefore, we conducted robustness check to further confirm the findings about the effect of policy change.

Given that the experiment lasted for three weeks, we created three new sub-samples by pooling each of the three weeks' transaction data with the data from pre-experiment period. If the observed treatment effect from Table 5.2 as well as Table 5.3 and 5.4 is due to Hawthorne effect, we would expect the price increase diminish over time (Clark and Sugrue, 1988). Thus we re-estimated the model in Equation 5.1 on the three sub-samples. Table 5.6 summarizes the estimation results. Overall, we can see that the treatment effect remains positive and significant over the three weeks: in Week 1, the average price increased by 1.9 % under the treatment condition whereas in Week 2 and 3, price increased by 5.1%, thus providing further assurance that our main results in Table 5.2 are robust.

Table 5.6: Results of robustness check on the sub-samples.

Coefficient	Week 1 (Nov.19-23)		Week 2 (Nov. 26-30)		Week 3 (Dec. 3-7)	
	Estimate	P-value	Estimate	P-value	Estimate	P-value
Treatment period (β_1)	0.210	0.000 ***	0.200	0.000 ***	-0.026	0.000 ***
Treatment (β_2)	-0.044	0.011 *	-0.010	0.561	0.042	0.020 *
Treatment period * Treatment site (β_3)	0.019	0.015 *	0.051	0.000 ***	0.051	0.000 ***
Adjusted R^2 : 0.202		Adjusted R^2 : 0.210		Adjusted R^2 : 0.127		

5.5.3 Additional Analysis

So far, our analysis shows that bidders paid significantly higher prices under the treatment condition, regardless of the market channels they chose. A natural question is why bidders paid more when the winners' identities were concealed.

Given that bidders in this market have been competing in these auctions repeatedly for a long period of time and many of them know each other very well, it is possible that some bidders might engage in tacit collusion, i.e., coordination between several competing players (typically large ones) without overt communication or agreement (Bajari and Yeo, 2009; Sherstyuk and Dulatre, 2008). There are two essential elements for tacit collusion: 1) a transparent mechanism for coordinating on a collusive outcome; and 2) a plausible amount of mutual understanding among firms (Harrington, 2012). For example, if two large bidders always end up in competing for products from the same supplier, they might be have the incentive to implicitly coordinate their bids.. For example, if two large bidders always end up in competing for products from the same supplier, they might be better off by coordinating their bidding behavior. If this is the case, the public signal of winners' identities would be indispensable to the stability of the cartels – the defect member (bidders who did not follow the collusive strategy) could easily be identified and punished by other members within the cartel. This rationale leads to the following hypothesis:

H1: Bidders with a higher tendency to engage in tacit collusion pay lower prices when winners' identities are disclosed.

In order to test this hypothesis, we first need to quantify bidders' tendency of collusion. We define a bidder's *collusion index* as the inverse of the total number of suppliers from whom he made purchases. The larger a bidder's collusion index is, the higher his tendency of collusion¹². We then classify bidders into two types – the ones with high tendency to collusion and those with low tendency to collusion – using the median of the collusion index for all bidders during the pre-experiment period.

We use the following hierarchical model to test the above hypothesis:

$$\text{Level 1 : } \log P_{i,j,t} = \beta_{0,j} + \beta_1 T_t + \beta_2 G_i + \beta_{3,j} G_i * T_t + \gamma X_{i,t} + \epsilon_{i,j,t}, \quad (5.3a)$$

$$\text{Level 2 : } \beta_{0,j} = \alpha_{00} + \alpha_{01} H_j + u_{0,j}, \quad (5.3b)$$

$$\beta_{3,j} = \alpha_{30} + \alpha_{31} H_j, \quad (5.3c)$$

where H_j is a dummy variable, $H_j = 1$ if bidder j is classified as having high tendency of collusion. The estimation results are shown in Table 5.7.

¹²Here, the basic idea is that a bidder is more likely to engage in tacit collusion if he always purchases from a small number of suppliers.

Table 5.7: Impact of policy change on potential bidder collusion.

Coefficient	Estimate	Std. error	P-value
Collusion tendency (α_{01})	-0.098	0.006	0.000 ***
Treatment period (β_1)	0.127	0.003	0.000 ***
Treatment site (β_2)	-0.002	0.012	0.858
Treatment period * Treatment site (β_3)	0.042	0.005	0.000 ***
Collusion tendency * Treatment period * Treatment site	0.035	0.013	0.009 **
Adjusted R^2 : 0.190			

We can see that bidders with higher tendency of collusion indeed pay significantly lower (9.8%) prices when winners' identities are disclosed. Thus H1 is supported. Further, Table 5.7 shows that the "advantage" of these bidders is mitigated under the treatment condition, suggesting that withholding winners' identities can reduce the potential tacit collusion.

5.6 Discussion

5.6.1 Key Findings

Our paper offers several findings with regard to information transparency strategies in sequential auctions. First, we find that overall, bidders tend to pay higher prices when the identities of winners from previous (sub)auctions are not publicly disclosed. Such positive effects hold for both online and offline bidders. This means that the weak signals or the increased market state information available in the auction room cannot compensate for the loss of the information associated with winners' identities. At the outset, this finding contradicts the predictions of linkage principle, which suggests that releasing more information can increase sellers' revenue. Therefore, it calls for finer-grained models to characterize the bidding dynamics in real-world multi-unit sequential auctions.

Further, we provide empirical evidence of declining price anomaly under two revelation policies and show that the less transparent policy can mitigate the price declining trend. Such finding to a large extent confirms the direct-learning effect in sequential auctions (Jeitschko, 1998). In other words, bidders base their inferences of the market trend not only on the revealed prices in previous rounds, but also the revealed winners' information. Thus it sheds new lights on the explanations to declining price anomaly (Van den Berg et al., 2001). We also explore the potential explanations to the observed price increase associated with the policy change by examining bidders' tendency to commit tacit collusion. Our results show that bidders who stick to a small set of trading partners and thereby have higher tendency to collude incur a significant

loss of surplus under the less transparent setting. This suggests that winners' identities might be used to enforce the agreement within cartels and deter each other from bidding high.

5.6.2 Contribution

Our findings contribute to the existing literature on information disclosure in auctions. Previous studies on information revelation policies are largely restricted to analytical modeling where bidders are assumed to be fully rational or lab experiments where bidders are typically less experienced. Our research complements them by bringing richness of real-world operation environments while maintaining a high level of control. In addition, despite the growing interest in information revelation policies in online auctions, for example, Arora et al. (2007); Granados et al. (2010); Greenwald et al. (2010), most of the existing research focuses on price and product transparency. We provide a different perspective to examine the linkage principle and the current debate between transparency strategies.

The findings from our study also provide important implications to practice. Previous research has shown that sequential auctions are more susceptible to collusion as compared to simultaneous auctions (Sherstyuk and Dulatre, 2008). Thus how to effectively detect collusive bidding and deter future collusion is a major issue in the practical design of sequential auctions. In our study, we find that withholding winners' identities in sequential auctions can reduce the potential tacit collusion. In fact, the results from our analysis shows that bidders with higher tendency of collusion is expected to pay significantly higher when winners' identities were not communicated publicly.

As Koppius (2002) points out, information architecture –“what type of information is available to whom, or when and how it becomes available to whom during the market process”– is important for the performance of auctions. With the ongoing trend of moving from place to space (Kuruzovich et al., 2008), choosing appropriate information revelation policy across different market channels becomes even more critical in the design of these multi-channel auctions. Note that although online channels could in principle encourage entry by breaking the physical limitations such as time and space and bringing millions of globally dispersed business entities to the trading activities in auctions, the enhanced communication capabilities resulting from online channels also facilitate collusive behavior. Therefore, market designers must weigh the benefits and threats carefully when disclosing any product- or market-related information.

5.6.3 Limitation and Future Work

The current study bears several limitations. For example, due to practical constraints, we could not extend the experiment period to a longer time and as the result, we were not able to examine

whether the increase in transaction prices is persistent, or bidders' behavior might gradually converge after a longer time and the price will fall back to the pre-experiment period (when other factors are controlled). Additionally, we could not infer the complementarity or substitutability of different products from the current dataset and take them into account in the DID model. If there was a demand shock of another product which serves as a complement of the product chosen in our analyses, it would have led to an overestimation of the actual effect of the policy change. However, there is no particular evidence of such demand shock, nor significant change in bidders' bidding patterns (see Table 5.1). Therefore, this is not a big concern in this paper. Future work can take transaction data from multiple types of products to verify the robustness of our results.

A number of directions are possible as the extension of the current research. Our current analysis only suggests that bidders with higher tendency of tacit collusion pay lower prices under the high-transparent situation (i.e., when winners' identities are disclosed) and incur a substantial loss of surplus under the low-transparent situation. It is interesting to identify and understand the intermediate mechanism by which those bidders acquire and lose the advantage. Further, given that these are B2B auctions, it is also necessary to examine the impact of the policy change to the post-auction trades. For example, it is much more difficult for the customers of a bidder to trace the original purchasing prices in the auction market. This might provide the bidder an opportunity to maximize his profit margin and thus affect his bidding strategies in the auctions. An integrated model which incorporates the post-auction competition can be very helpful in understanding the impact of different revelation policies in the whole supply chain.

5.6.4 Concluding Remark

We study the impact of different information revelation policies in sequential B2B auctions using field experiment. Our analyses document a significantly positive effect on transaction prices associated with the less-transparent policy which conceals winners' identities. This result suggests that higher transparency might, despite all the well-known advantages, facilitate tacit collusion and mitigate competition.

Chapter 6

Conclusion

In this chapter, we first summarize the findings from the three specific studies and then continue with a discussion of the theoretical contributions and managerial implications. Finally, we also reflect on the limitations of the current research and present an outline for future work.

6.1 Main Findings

Our central research question is how to leverage the power of data to improve the design and operationalization of complex auction markets. We address this question by systematically examining the interplay of different informational and strategic factors in three specific studies.

Adaptive Design. In Chapter 3, we develop a structural econometric model to understand the effect of auction design parameters on sellers' revenues. By recovering bidders' value distribution and their bidding functions under different market conditions, we empirically demonstrate the influence of auction design parameters on bidders' willingness-to-pay and market clearing speed. Specifically, we find that increasing minimum purchase quantity can speed up the market clearing process significantly, albeit the considerable cost in revenue. In light of this, we develop a dynamic optimization approach which makes use of the rich structural properties identified from historical data to guide auctioneers in setting the auction design parameters. Based on our simulation results, such data-driven optimization approach can help to generate significantly higher revenue while maintaining a high throughput. Therefore, it has great promises in facilitating auctioneers' real-time decision making.

Bidder Heterogeneity. Chapter 4 examines bidders' strategic decisions across different market channels. Using a unique and extensive data set which contains transaction details from both online and offline channels, we find a stable taxonomy which consists of five types of bidding strategies. Although some of the strategic types bear similarities with those identified

from B2C context (Bapna et al., 2004; Goes et al., 2012), we also observe interesting nuances. For example, on average, neither *opportunistic bidders* nor *early evaluators* won in more than one auction on any given day. This reflects the fundamental difference in bidders' incentive structure in B2B and B2C markets. Additionally, given that all the bidders in our case have rich bidding experience, the existence of these distinct bidding strategies challenges the common notion that bidders' strategies will converge as they gain experience, suggesting that we should pay more attention to the economic factors, for example, bidders' budget constraints and transaction costs, instead of the process-dependent factors such as bidders' participation or winning experience in B2B auctions. We also perform outcome analysis on different strategic types and examine their interactions with key auction design parameters such as lot size and minimum purchase quantity. The results from our analysis show that *opportunistic bidders* perform best in minimizing their loss-of-surplus. Further, we find significant moderating effects of lot size and minimum purchase quantity on bidding strategies. These findings reinforce the importance of real-time segmentation of bidder population in these sequential auctions.

Information Transparency. Chapter 5 investigates the impact of information revelation policy on price dynamics and market outcome. Using a field experiment, we find that bidders tend to pay higher prices when the identities of winners from previous (sub)auctions were concealed from public view. Such positive effect holds for both online and offline bidders, suggesting that the weak signals or the increased market state information from the offline channel (auction rooms) cannot compensate for the loss of the additional information conveyed via winners' identities. In addition, our analysis shows that anonymizing the winning bids can also mitigate the price declining trend in sequential rounds.

At the outset, our finding contradicts the prediction of the linkage principle, which states that sellers are better off by revealing more information to bidders. Since previous research suggested that linkage principle can fail if bidders cooperate in the bidding process, we created a proxy of bidders' tendency of tacit collusion in these auctions and compared the average prices paid by bidders with high and low tendency of tacit collusion under different revelation policies. The result shows that bidders with high tendency of collusion paid significantly lower than those with low tendency of collusion when winners' identities are disclosed. However, when the winning bids were anonymized, such advantage associated with the potential tacit collusion diminished substantially.

Overall, we have illustrated and quantified the benefits of data-driven decision making in dynamic, complex auction markets. Figure 6.1 depicts a conceptual model of data-driven decision making in these markets. Here, bidder type is determined by the business characteristics of

a bidder, for example, his budget constraint, channel affiliation. Market process is defined as the processes of information exchange in the market. Market outcome refers to the transactions that result from the market process. Both market process and market outcome are descriptive (Koppius, 2002). Data analytics refers to the practice of collecting, evaluating and analyzing data to inform decisions. This include different types of analytical models, as well as advanced computational tools such as agent-based simulations (Ketter et al., 2012).

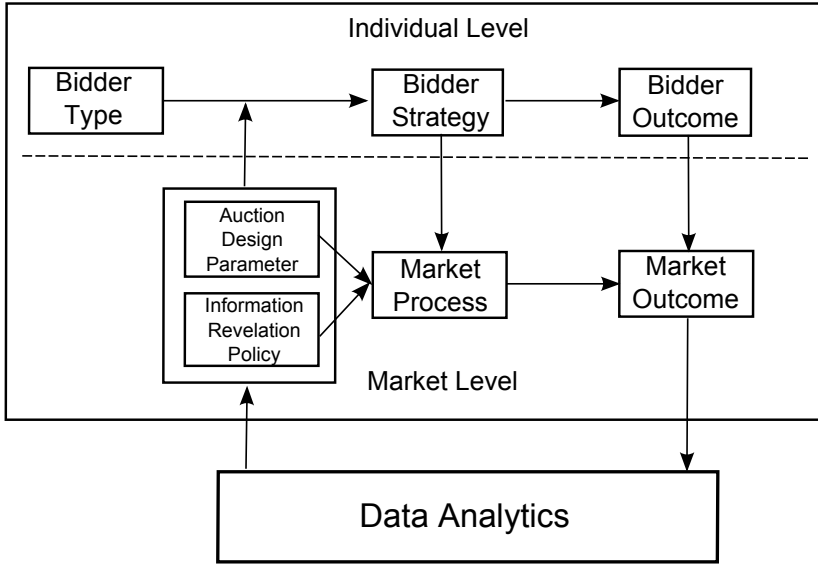


Figure 6.1: A conceptual model of data-driven decision-making in auction markets.

6.2 Scientific Contributions

This dissertation makes valuable contributions to the empirical auction literature. First of all, the three specific studies (Chapter 3, 4 and 5) together have greatly improved our understanding of real-time bidding in complex auction markets. To the best of our knowledge, this is the first research that systematically examines the interplay of informational and strategic factors in multi-channel B2B auction market. Second, our findings offer a high level of granularity to the general principles for auction design, i.e., encourage competition and discourage collusion. Third, this research also shed new lights on some interesting phenomenons which have attracted the attention of auction researchers for long (e.g., declining price anomaly, linkage principle).

Further, it also contributes to the nascent literature of smart markets (Bichler et al., 2010). In particular, the dynamic optimization approach proposed in Chapter 3 serves as a useful starting

point for the development of real-time decision support systems for auctioneers. In addition, the bidder taxonomy developed in Chapter 4 can be viewed as a micro-segmentation of the bidder population, which is the prerequisite for the customization of design parameters as well as information strategies across different channels.

Finally, our research makes important methodological contribution. Specifically, in Chapter 3, we extended the existing structural models to explicitly address the sequential aspects and bidders' multi-unit demand in each round. Currently, most of the structural modeling work focuses on single-unit auctions, for example, Donald and Paarsch (1996); Guerre et al. (2000); Laffont and Vuong (1995); Paarsch (1997). Of the few papers which investigated multi-unit sequential auctions (Brendstrup, 2002; Brendstrup and Paarsch, 2006; Jofre-Bonet and Pesendorfer, 2003), bidders are either assumed to have single-unit demand throughout an auction or they can acquire at most one unit in each round. Relaxing the single-unit assumption introduces a number of econometric and computational challenges to the structural modeling of sequential auctions. We exploit the unique features of the empirical auction environment to model bidders' sequential decision-making process. In order to estimate the key parameter of the model, i.e., the number of bidders in each round of the sequential auctions, we developed an iterative method using simulations. The extensive modeling effort has led to many new insights about multi-unit sequential auctions. In addition, we have combined machine learning techniques with advanced statistical models to explore bidder heterogeneity in Chapter 4. Finally, in Chapter 5, we applied one of the state-of-the art techniques (i.e., difference-in-differences) to identify the causal effect of information revelation policy change using the experiment data.

6.3 Managerial Implications

Our research suggests that theoretically guided computational tools have great promise in facilitating the design and operationalization of complex auction markets. In order to address the cognitive and computational limitations of human decision makers in their real-time decision making process, we propose to augment their judgment with high-performance decision support tools in the form of software agents (Wooldridge and Jennings, 1995). These agents will assist users in a collaborative manner, gathering and presenting information and recommending actions. In order to be helpful, these agents should have the following core capabilities:

- Identification of the structural properties. The software agent can identify the structural properties such as bidders' value distribution from all the available information in the market, for example, winning bids and purchase quantities in previous transactions.
- Prediction of the future auction states. As soon as the agent learns the structural properties

of the underlying auction model, it can make predictions of future prices, purchase quantities as well as the market trends (Ketter et al., 2012). Although existing approaches for price prediction vary considerably, it has been widely recognized that predictions should exploit all the available information and take the market structure (bidder segmentation) into account.

- Optimization of the auction design. Based on the prediction of the future states, the agent can dynamically set the key auction parameters and choose information revelation policy with respect to some performance metrics (for example, seller revenue). In addition, the agent can communicate with the human user about such performance metrics at any point of the sequential auction and adjust the optimization process accordingly.

Although the dynamics of auctions are the immediate context of this research, we can interpret individuals' bids as examples of important individual or organizational decisions. For example, many organizations participate regularly in auctions as they compete for contracts or projects, and executives and management teams often find themselves caught in a bidding war to acquire companies or to hire new talents. In addition, information overload is not only restricted to the auction market. As Simon (1971) said, "a wealth of information creates a poverty of attention and a need to allocate that attention efficiently among the overabundance of information sources that might consume it." In this regard, this research has useful implications for understanding a broad spectrum of decision-making processes in real-world business environments.

6.4 Limitations

The current research adopts a multi-method approach to examine the real-time decision making in auction markets. The combination of different methods such as structural modeling, simulation and field experiments leads to a higher validity as compared to research which employs a single method. That said, this research still bears several limitations.

To start with, we chose a specific type of product in each of the three specific study. However, as we discussed in Chapter 4, in reality, there is substitutability or complementarity between different products, and this clearly influences bidders' bidding decisions. However, since we did not have access to bidders' order-books, nor the general information about their preferences towards different product assortments, it was not possible to control for this factor in modeling or clustering of bidding strategies. This might distort some of our findings in Chapter 3 and Chapter 4.

Second, when modeling the real-time bidding in these multi-channel auctions, we exclude

transactions made when the market was likely to experience a shock due to demand surge (for example, on Valentine's Day), supply plunge, or other internal and external factors. Here, our main concern is that these market shocks might result in severe behavioral shocks (See the discussion in Section 3.5.2) that must be isolated and studied separately from the regular bidding decision making in the market. Since in this research we are more interested in identifying the *regularities* of these complex markets and quantifying the value of data-driven decision making, we think such simplification is appropriate, although it may limit the prediction power of our models.

Third, we did not consider the influence of post-auction markets on bidding strategies in the analysis of information transparency (Chapter 5). However, According to Chen and Vulcano (2009), the information disclosed in the upstream auctions can affect the profitability in the downstream resale markets. They have found that the risk of revealing private information in the downstream resale market induces lower bids than the ones that would be submitted under conventional auctions without post-auction markets. Following this rationale, we might have alternative explanations to the findings in Chapter 5. In particular, under the current auction practice, winners' identities are disclosed during the auction phase. Given the B2B nature of these auctions, this means bidders incur the risk of exposing themselves to their direct competitors as well as customers in the resale markets. To mitigate such threat, bidders shade their bids more under higher transparent condition. With the current evidence, we cannot tell which is the main driver of the price increase observed in the experiment period, the post-auction market effect or the potential collusion effect, or both. Nevertheless, this limitation, just as the others mentioned above, also opens up avenues for future research.

6.5 Future Work

We conclude this dissertation with an outline for future work. First of all, in order to address the aforementioned limitations, we need to extend our current models to accommodate the real-world complications. In most cases, the traditional game-theoretic models are insufficient to guide the practical design. In light of this, an interesting direction to pursue is to develop rich simulation platform which allow us to create different bidder profiles and experiment with alternative auction designs under different information revelation policies. This can help us develop better understanding of the interplay of different informational and strategic factors in real markets and thus lead to more useful implications for practice.

Further, as Smith (1990) states, "auctions are social processes capable of defining and resolving inherently ambiguous situations, especially questions of value and price." Given the B2B nature of these auctions, both bidders' decisions and market outcomes are influenced by

the social structure. This suggests that we should adopt a social embeddedness approach (Granovetter, 1985) and look into the social relations or networks within this market. In this sense, the study in Chapter 5 only touched upon the surface of this topic by examining the potential collusion. Much more work remains to be done.

The massive data generated from different markets provides ample opportunities for both businesses and academics. However, the full exploitation of these opportunities requires not only the understanding of general principles that govern the specific market, but also the development of advanced modeling and computational tools. Therefore, we as information systems researchers need to work closely with scholars from other areas such as economics, computer science, and operations management, as well as practitioners from different application domains.

Summary

Over the past decades, the increased accessibility of data has enabled a different way of making decisions that involves more empirical evidence rather than intuition and experience. Such data-driven decision making has attracted a growing interest from both business practitioners and academic researchers. This dissertation consists of three specific studies that illustrate and quantify the benefits of data-driven decision making in the design and operationalization of complex auction markets.

In the first study (Chapter 3), we derive a structural econometric model to understand the effect of auction design parameters on sellers' revenues. By recovering bidders' value distribution and their bidding functions under different market conditions, we are able to empirically measure the impact of auction design parameters on bidders' willingness-to-pay and market clearing speed. We also develop a dynamic optimization approach which makes use of the rich structural properties identified from historical data to guide auctioneers in setting the key auction parameters. Based on the simulation results, such data-driven optimization approach can help to generate significantly higher revenue while maintaining a high throughput and thereby, has great promises in facilitating auctioneer's real-time decision making.

In the second study (Chapter 4), we explore bidding strategies in a multi-channel B2B market. Using a unique and extensive data set which contains transaction details over a long period of time, we find a stable taxonomy which consists of five distinct types of bidding strategies. Although some of the strategic types bear similarities with those identified in previous studies of B2C markets, we also observe interesting nuances. We also perform outcome analysis on different strategic types and examine their interactions with auction design parameters. Our findings reinforce the importance of real-time segmentation of bidder population in these sequential auctions.

In the third study (Chapter 5), we investigate the effect of information revelation policy on price dynamics and market performance. Using a field experiment, we find that bidders tend to pay higher prices when the identities of winners are concealed from public view. Such positive effect holds for both online and offline bidders, suggesting that the weak signals or the increased market state information from the offline channel cannot compensate for the loss of

the additional information conveyed via winners' identities. In addition, our analysis shows that anonymizing the winning bids can also mitigate the price declining trend in sequential rounds.

Overall, this research offers important implications to both theory and practice of decision-making in complex, dynamic markets. From the theoretical perspective, this is, to our best knowledge, the first research that systematically examines the interplay of different informational and strategic factors in multi-channel auction markets. In particular, it sheds new light on real-time decision support in complex markets and thus contributes to the nascent literature of *smart markets*. From the managerial perspective, our research shows that advanced data analytics tools have great potential in facilitating decision-making in complex, real-world business environments.

Samenvatting

In de afgelopen decennia heeft de toegenomen toegankelijkheid van gegevens een andere manier mogelijk gemaakt van het nemen van beslissingen die meer gebruik maken van empirisch bewijs in plaats van persoonlijke ervaring, intuïtie, of bepaalde overtuigingen. Dergelijke data gedreven besluitvorming is aan een groeiende belangstelling van zowel zakelijke professionals als academische onderzoekers onderhevig. Deze dissertatie bestaat uit drie specifieke studies die de meerwaarde van data gedreven besluitvorming illustreren en kwantificeren bij het ontwerp en de operationalisering van complexe veilingen.

In de eerste studie (hoofdstuk 3), leiden we een structureel econometrisch model af om het effect van ontwerp keuzes op de omzet van verkopers. Door het vinden van de waarde distributie van bidders en de manier waarop ze bieden onder verschillende marktomstandigheden, meten we empirisch de impact van de veiling ontwerp keuzes op de bereidheid-tot-betalen van bidders en de transactie snelheid. We ontwikkelen ook een dynamische optimalisatie methode die gebruik maakt van de rijke structurele eigenschappen die geïdentificeerd zijn aan de hand van historische gegevens om veilingmeesters te begeleiden bij het maken van de belangrijkste keuzes betreffende het design van een veiling. Op basis van de resultaten van de simulatie, maakt een dergelijke data gedreven optimalisatie benadering aanzienlijk hogere opbrengsten mogelijk met behoud van een hoge doorvoer en heeft daardoor grote potentie in het faciliteren van de real-time besluitvorming van de veilingmeester.

In de tweede studie (hoofdstuk 4), onderzoeken we biedstrategieën in een B2B markt met meerdere afzetkanalen. Met behulp van een unieke en uitgebreide dataset die transactiegegevens over een lange tijdsperiode bevat vinden we een stabiele taxonomie die bestaat uit vijf verschillende soorten biedstrategieën. Hoewel sommige van de strategische types gelijkenissen vertonen met de types die geïdentificeerd werden in de eerdere studies van de B2C context, zien we ook interessante nuances. We analyseren ook de impact van de verschillende strategische soorten gedrag en onderzoeken de interactie tussen deze en de veiling ontwerp keuzes. Onze bevindingen versterken het belang van real-time segmentatie van de bidder populatie in deze sequentiële veilingen.

In de derde studie (hoofdstuk 5), onderzoeken we het effect van het beleid ten aanzien van

openbaring van informatie op de prijs dynamiek. Met behulp van een veldexperiment vinden we dat bieders de neiging hebben om hogere prijzen te betalen als de namen van de winnaars afgeschermd zijn. Dit positieve effect gaat zowel op de online als de offline bieders, wat suggereert dat de zwakke signalen of de toegenomen informatie over de markt van het offline kanaal niet kan compenseren voor het verlies van additionele informatie die overgebracht werd door de identiteiten van winnaars. Bovendien blijkt uit onze analyse dat het anonimiseren van het winnende bod de dalende trend in de prijs kan verzachten door de identiteiten van winnaars te verhullen in opeenvolgende ronden.

Kortom, dit onderzoek draagt belangrijke implicaties bij aan zowel theorie als praktijk van besluitvorming in complexe, dynamische markten. Vanuit het theoretisch perspectief is dit, zover wij weten, het eerste onderzoek dat systematisch de wisselwerking tussen verschillende informatieve en strategische factoren onderzoekt bij veilingen met meerdere afzetkanalen. In het bijzonder werpt het een nieuw licht op de real-time ondersteuning van de besluitvorming in complexe markten en draagt het zo bij aan de literatuur in wording over smart markets. Qua relevantie voor de manager, toont ons onderzoek aan dat geavanceerde data analyse een grote potentie heeft in het faciliteren van de besluitvorming in de complexe, zakelijke omgeving.

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About the Author



Yixin Lu was born on May 17, 1984 in Zhejiang, China. She studied Applied Mathematics at Chu Kochen Honors College of Zhejiang University and graduated *cum laude* in 2006. In the same year, she was awarded an Erasmus Mundus scholarship by European Commission and started her master in Industrial Mathematics at Technical University of Kaiserslautern, Germany and Eindhoven University of Technology, Netherlands. She obtained the double master degree *cum laude* in 2008. From 2008 to 2009, she worked as a scientific consultant at Laboratory for Industrial Mathematics Eindhoven (LIME).

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Selected Publications

Lu, Y., A. Gupta, W. Ketter, and E. van Heck. “Information Transparency in B2B Sequential Auctions,” *the 10th Symposium on Statistical Challenges in eCommerce Research (SCECR)*, Tel Aviv, Israel, June, 2014

Lu, Y., A. Gupta, W. Ketter, and E. van Heck. “Designing Intelligent Software Agents for B2B Sequential Dutch Auctions: A Structural Econometric Approach,” *the 34th International Conference on Information Systems (ICIS)*, Milan, Italy, December, 2013.

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Lu, Y., A. Gupta, W. Ketter, and E. van Heck. “Flexible Decision Support in Multi-Unit Sequential B2B Auctions: A Structural Estimation Based Framework,” *the 9th Symposium on Statistical Challenges in eCommerce Research (SCECR)*, Lisbon, Portugal, June, 2013

Lu, Y., P. van Iterson, A. Gupta, W. Ketter, J. van Dalen and E. van Heck. “Buy It Now or Later: The Impact of *Mari* on Multi-unit Sequential Dutch Auctions,” *Winter Conference on Business Intelligence*, Snowbird, USA, March, 2013.

Lu, Y., A. Gupta, W. Ketter, and E. van Heck. “Exploring Bidder Heterogeneity in B2B Auctions: Evidence from the Dutch Flower Auctions,” *Conference on Information Systems and Technology (CIST)*, Phoenix, USA, October, 2012. **Best Student Paper Nomination.**

Lu, Y., W. Ketter, J. van Dalen, A. Gupta, and E. van Heck. “A Stochastic Model of Winning Bids in the Dutch Flower Auctions,” *the 8th Symposium on Statistical Challenges in Electronic*

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DATA-DRIVEN DECISION MAKING IN AUCTION MARKETS

This dissertation consists of three essays that examine the promises of data-driven decision making in the design and operationalization of complex auction markets. In the first essay, we derive a structural econometric model to understand the effect of auction design parameters on sellers' revenues. In addition, we develop a dynamic optimization approach which makes use of the rich structural properties identified from empirical data to guide auctioneers in setting these parameters in real-time. In the second essay, we focus on bidding strategies across different market channels and examine the interactions between different strategies and auction design parameters. In the third essay, we investigate the effect of information revelation policy on price dynamics and market performance. This research offers important implications to both theory and practice of decision-making in information-rich and time-critical markets. From the theoretical perspective, this is, to our best knowledge, the first research that systematically examines the interplay of different informational and strategic factors in dynamic, multi-channel auction markets. In particular, it sheds light on real-time decision support in complex markets and thus contributes to the nascent literature on *smart markets*. From the managerial perspective, our research shows that advanced data analytics tools have great potential in facilitating decision-making in complex, real-world business environments.

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